Essays on banking, financial intermediation and financial markets

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door

NESTOR MIGUEL SARMIENTO PAIPILLA
geboren op 17 december 1979 te Bogotá, Colombia.

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COPROMOTOR: dr. Olivier De Jonghe

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prof. dr. Hans Degryse
prof. dr. Sylvester Eijffinger
prof. dr. Wolf Wagner

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The main question in the Chapter 3 came to my mind in the summer of 2016 during the annual meeting of the IFABS in Barcelona. Because of I was selected to be the chair of the session, I had to carefully read all the four papers of the session to have ready a couple of questions of each paper to motivate the discussion in the auditorium. One of those questions was: How banks will react to liquidity shocks in the interbank market? The answer I received from the presenter was: It will be an interesting aspect to explore but it is beyond the scope of the paper! So, I tried to incorporate this new element in my analytical framework following the suggestions of Harry and Wolf. Then, I had the chance to participate with this paper in a visiting program sponsored by the Graduate Institute of International and Development Studies (IHEID) in Geneva and the Swiss Economics Secretariat (SECO). During my visit to Geneva, I had the fortune to know Yi Huang who motivated me to work on the role of the spillover effects from the U.S. monetary policy in emerging markets. That was not only the second type of shock that I incorporated in this chapter, but also new project that we have been developing with Daniel Dias (my former professor at UIUC) and Hélène Rey (one of the most influential academics in this filed) from the London Business School.

The Chapter 4 was initiated during my visiting position at the International Monetary Fund (IMF) between 2016 and 2017. I remember that my initial idea was to extend the analytical framework of Chapter 2 by incorporating the role of competition and stability. However, I was encouraged to think out of the box by testing the market discipline hypothesis (the chief hypothesis in Chapter 3) using a very rich data set of the cross-border syndicated loan market.

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Miguel Sarmiento
Bogotá, May 2019

Contents

1. Introduction

1.1. Motivation

Financial intermediaries interact across different markets in order to diversify risk exposure and to get funding from alternative sources. While this can increase bank efficiency and alleviate financial intermediation costs, it makes more difficult the effective regulation and supervision of banks and can expose them to liquidity shocks and contagion risk (Allen and Gale, 2000; Upper and Worms, 2004; Laeven and Levine, 2009). During the global financial crisis (GFC) of 2007-08 the interaction of banks across different markets was insufficient to assure the necessary liquidity for the normal operation of the banking system. Financial intermediaries operating in the U.S. exhibited fire-sales and liquidity hoarding (Brunnermaier 2009, Shleifer and Vishny, 2010), as evidence of the *rational uncertainty* that dominated the behavior of markets' participants (King, 2016).[1] In particular, the availability of short-term liquidity from the unsecured interbank market was severely affected (i.e. via credit rationing and higher loan rates) due to an external shock that took place in another market—the sub-prime market of mortgage back securities (MBS)—(Angelini et at. 2011; Afonso et al. 2011). In order to alleviate liquidity tensions in the interbank markets, the Fed had to create new liquidity facilities and grant liquidity throughout large-scale purchases of assets (i.e. the quantitative easing).

However, the unconventional monetary policy adopted in the U.S—and since 2010 in the Eurozone—had spillover effects on emerging markets. Recent evidence suggests that the large liquidity provided by the Fed and ECB increased global liquidity and lead to search-for-yield in emerging economies (Morais et al. 2017; Rey, 2016; Fratzscher, et al. 2016; Demirgüç-Kunt, et al. 2017). Furthermore, the monetary policy normalization—initiated in May 2013 with the U.S. tapering—motivated a flight-to-home effect that resulted in capital outflows, exchange rate depreciation, and increased funding costs in emerging economies (Eichengreen and Gupta, 2015; Bouwman et al. 2015; Aizenman et al. 2016). As a result, emerging economies have been

[1] King (2016) highlights the weakness of the financial industry' risk assessment and its consequences over the financial markets based on the concep of radical uncertainty. In particular, he argues that: "radical uncertainty makes it likely that from time to time there is a revision in the narrative guiding investor behavior, or in the coping strategy as a whole, leading to sharp changes in traders' perception of values and willingness to buy or sell financial assets".

forced to implement macroprudential measures—including capital controls—to limit the exposition of the banking sector to the international monetary policy shocks, and to gain monetary policy autonomy (Forbes et al. 2016; Dias et al. 2018).

This dissertation evaluates the behavior of banks across the financial markets and proposes alternative methods to identify the way interconnectedness, risk taking, regulation, and liquidity shocks can affect their behavior, and performance. Additional elements for the implementation of monetary policy and for and for enhancing financial stability and access to finance are provided.

1.2. Contributions

In Chapter 2 we propose an alternative approach to study the allocation of central bank liquidity among the participants of the unsecured interbank market. Using network topology metrics and micro-data on repo and unsecured interbank loans from the central bank of Colombia during 2010-2013, we identify the super-spreaders of the central bank liquidity within the unsecured interbank market.[2] We find an inhomogeneous and hierarchical connective (core-periphery) structure, in which a few financial institutions fulfill the role of super-spreaders of central bank's liquidity within the interbank funds market; that is, we identify those financial institutions that excel as global borrowers and lenders.

This chapter contributes with new tools to examine and understand the structure and dynamics of interbank funds' networks. The resulting insights are important for the implementation of monetary policy and safeguarding financial stability. One the one hand, we find evidence supporting the key role of some financial institutions as super-spreaders of the central bank's liquidity, which improves the implementation of monetary policy. On the other hand, testing that the probability of being a super-spreader in the Colombian case is determined by financial institutions' size further supports some of the most salient findings of interbank relationships literature (see, Cocco et al. 2009, Fecht et al. 2011; Afonso et al. 2013). That is, lending

[2] Under our analytical framework, a financial institution may be considered a super-spreader for central bank's liquidity if it simultaneously excels at distributing liquidity to other participants (i.e. it is a good hub) and it excels at receiving liquidity from good hubs (i.e. it is a good authority), with the central bank being among the best hubs.

relationships are motivated by too-big-to-fail implicit guarantees. Thus, the larger the bank is, the more interconnected and central it is in the interbank network. This result implies greater concentration in the network of financial connections that can amplify contagion effects.

In Chapter 3, we employ a stochastic frontier model with random inefficiency parameters to identify the heterogeneous effects of risk taking on bank efficiency. The proposed approach contributes to the recent literature devoted to model the role of risk taking in explaining bank efficiency (Hughes and Mester, 2013; Pessarossi and Weill, 2015). We use bank-level data of the Colombian banking system for the period 2002 to 2012, a period in which several regulatory measures to promote the foreign entry of banks and to limit bank risk-taking—prior to the GFC—were implemented.

The results highlight the importance of accounting for size, affiliation and risk exposure in the estimation of bank efficiency. We find that cost and profit efficiency are over-underestimated when risk measures are not properly modeled. Interestingly, we observe that size and foreign ownership are key determinants of efficiency, and also crucial characteristics determining the way changes in risk exposures affect bank efficiency. We identify that an ex-ante measure of credit risk captures better risk-taking incentives of banks than an ex-post measure such as nonperforming loans, and may provide regulators with a more suitable indicator for setting bank provisions for loan losses. This contributes to the recent debate on the role of bank loan losses provisions based on expected losses rather on incurred losses (see, Morais et al, 2018; Laeven and Huizinga, 2019). The results also support the hypothesis that capital requirements can contribute to enhance banking efficiency, especially for small and domestic banks (Berger and Bouwman, 2013).

Chapter 4 examines the impact of exogenous liquidity shocks on the access and pricing of funds in the unsecured interbank market. The main contribution consists in to evaluate the effects of both idiosyncratic and aggregate liquidity shocks in the unsecured interbank market, a market traditionally used for banks to cope liquidity shocks (Freixas et al. 2000) and that is highly influenced by peer monitoring (Rochet and Tirole, 1996). We use banks' deposits outflow as an approximation of idiosyncratic liquidity shocks, and the U.S. tapering—observed between May and September of 2013—as an aggregate liquidity shock. We employ a unique data set composed by non-publicly available data on daily overnight-unsecured bilateral loans among the financial institutions participating in the Colombian interbank market, which is matched with banks' daily liquidity reports (including access to CB repo operations) and monthly banks' balance sheet information to compute bank specific-characteristics related to liquidity, credit risk, size, and capitalization. The detailed information at the borrower, lender and loan level allow us to control for unobserved heterogeneity, isolate aggregate changes in liquidity, and disentangle supply from demand effects.

The results indicate that both liquidity shocks are associated with higher interbank loan prices, albeit the magnitude on the spread and the impact on the access to interbank liquidity differ depending on the borrower-specific characteristics. We observe that more capitalized and liquid banks not only tend to pay less for liquidity—evidencing the role of market discipline (Furfine, 2001; King, 2008)—, but also that they can absorb better the impact of exogenous liquidity shocks. Our results suggest that lending relationships can alleviate funding costs during idiosyncratic liquidity shocks (Afonso, et al. 2014), but are less effective during aggregate liquidity shocks, implying that hard information tends to overcome the benefits from private information during systemic liquidity shocks (Bednarek et al. 2015). We observe that the U.S. tapering had a significant effect on the prices of interbank funds in Colombia, consistent with the transmission of international monetary policy shocks (Rey, 2016; Fratzscher, et al, 2016), and that the central bank liquidity— which increased by 25% during the U.S tapering— contributed to mitigate the impact of this liquidity shock on funding costs in the interbank market. The mitigating role of central bank liquidity is consistent with the evidence observed during the GFC (Allen et al, 2009; Abbassi and Linzert, 2012), and can be related to the role of super-spreaders of central bank liquidity in Colombia (as shown in Chapter 2).

Chapter 5 examines the potential de-risking role of multilateral development banks (MDBs) in the cross-border syndicated lending market. Although there is an emerging empirical literature on the pricing of syndicated loans, the effect of MDBs' participation on loan pricing remains unexplored. This market is an important—and growing—source of external finance in many emerging and developing countries. Syndicated loans account for about one third of total cross-border lending between 1995 and 2012, on average (Cerutti *et al.*, 2015), and the size of the market is comparable to that of the bond market (World Bank, 2015). However, long-term financial flows to developing countries have been partly limited by high-risk perception and the resulting high cost of borrowing (Collier and Mayer, 2014). We use deal-level data on a large sample of about 17,000 syndicated loans granted to borrowers from 107 emerging and developing countries during the period 1994-2015. We investigate whether the presence of an MDB in the pool of lenders affect loan terms, especially loan pricing, and then check if MDB' participation mitigates borrower's riskiness, that can be translated into lower loan spreads.

We find that MDBs' participation is associated with higher borrowing costs and longer loan maturities. This finding indicates MDBs' higher capacity to lend at longer tenure than the private sector and—as long as spreads reflect borrower risk—the higher propensity of MDBs to finance risky projects—especially those in infrastructure—which may not be financed by the private sector. We also identify that the presence of an MDB in a syndicate is associated with a reduction of the effect of borrower riskiness on loan spreads by about one third. This suggests that MDBs' participation can lower borrowing costs for risky firms in emerging and developing countries, which could be the result of better information and monitoring of MDBs and the extension of their preferred creditor status (Arezki et al., 2017). We also find evidence on a countercyclical role of MDB participation, which can alleviate the flight-to-home effects observed after 2008.

1.3. Policy implications

This dissertation provides insights for the implementation of monetary policy, safeguarding of financial stability, and access to finance. First, it shows that a core-periphery structure of the central bank and interbank market network improves the implementation of monetary policy, but, at the same time, the greater concentration in the network of financial connections can amplify contagion effects.

Second, our findings suggest that capitalization can enhance bank efficiency. However, the gains from capitalization diminish as the benefits from bank size, and higher credit and market risk arise. Moreover, we show that large banks have higher incentives to engage on more credit and market risk, and benefit from lower funding costs—associated to too-big-to-fail implicit guarantees—, which contribute to explain why systemic risk can increase with bank size

(Laeven et al., 2016). These findings support the use of additional capital requirements for systemically important financial institutions.

Third, understanding the impact of exogenous liquidity shocks on the interbank market is crucial for identifying potential disruptions in the allocation of liquidity that could affect not only short-term funding, but also bank lending and monetary policy transmission. We observe that international monetary policy shocks have repercussions on the access and pricing in the interbank market in emerging economies. Our results suggest that capital and liquidity ratios contribute to increase the access to interbank liquidity during idiosyncratic liquidity shocks, while central bank liquidity contributes to alleviate funding costs during aggregate liquidity shocks. Thus, enhancing capital and liquidity regulation may contribute to monetary policy transmission a financial stability in emerging markets.

Fourth, we observe that cross-border syndicated lending allows financial intermediaries to diversity risks by increasing lending for borrowers located in emerging and developing countries. Our results suggest that MDBs play an important role in this market by lowering spreads to risky borrowers. Thus, risk mitigation can be a channel through which MDBs—thanks to better information and monitoring and the extension of their preferred creditor status—can crowd in private investment from advanced economies to emerging and developing countries.

The financial intermediation is subject to uncertainty from the depositors' and borrowers behavior. Financial markets are the scenario where such uncertainty takes place. The traditional risk measures employed until the GFC confirmed their lower efficacy in mitigating large financial shocks. Ten years after the GFC, banks have demonstrated that they can adjust their levels of liquidity, capitalization and loan provisions to their level of exposure (i.e. uncertainty). Recent prudential and financial regulation based on counter-cyclical capital requirements, long-term liquidity (i.e. net stable funding ratio) and loan provisions using expected losses (rather than incurred losses) are intended to limit bank risk taking and to account for the effects of domestic and global financial cycles. Evaluating how this new regulation can improve the resilience of the banking sector to domestic and external shocks—without affecting the benefits from the financial intermediation to the real sector—should be part of the future agenda of academics and policy makers.

Identifying Central Bank Liquidity Super-Spreaders in Interbank Funds Networks

2. Identifying Central Bank Liquidity Super-Spreaders in Interbank Funds Networks

Abstract

We model the allocation of central bank liquidity among the participants of the interbank market by using network analysis' metrics. Our analytical framework considers that a super-spreader simultaneously excels at borrowing and lending central bank's liquidity for the whole network, as measured by financial institutions' *hub centrality* and *authority centrality*, respectively. Evidence suggests that the Colombian interbank funds market exhibits an inhomogeneous and hierarchical network structure, akin to a core-periphery organization, in which a few financial institutions fulfill the role of central bank's liquidity *super-spreaders*. Our results concur with evidence from other interbank markets and other financial networks regarding the flaws of traditional direct financial contagion models based on homogeneous and non-hierarchical networks. Also, concurrent with literature on lending relationships in interbank markets, we confirm that the probability of being a super-spreader is mainly determined by financial institutions' size, but leverage and lending concentration as well. We provide additional elements for the implementation of monetary policy and for safeguarding financial stability.

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2.1. Introduction

The interbank funds market plays a central role in monetary policy transmission: it allows *banks to exchange central bank money in order to share liquidity risks* (Fricke and Lux, 2014). For that reason, *they are the focus of central banks' implementation of monetary policy and have a significant effect on the whole economy* (Allen et al. 2009; p.639), whereas the interbank rate is commonly regarded as central bank's main target for assessing the effectiveness of monetary policy transmission. In addition, as there are powerful incentives for participants to monitor each other, the interbank funds market also plays a key role as a source of market discipline (Rochet and Tirole, 1996; Furfine, 2001). However, the higher degree of interconnectedness in the interbank market makes it a potential source of bank contagion (Furfine, 2003; Upper and Worms, 2004). Thus, modeling the interaction among participants of the interbank market contributes to understand some of the recent disruptions that affected both the monetary policy transmission and the financial stability.

During the Global Financial Crisis (GFC) the interbank funds market exhibited a liquidity freezing in which money market primary dealers exerted market power and did not fulfill their role as liquidity conduits (Gale and Yorulmazer, 2013; Acharya et al. 2012). Moreover, increases in counterparty and liquidity risk were also associated with reduced lending activity within the interbank market (Beltran et al. 2015). Thus, identifying key players in the interbank funds market is important because their behavior contributes to determine the most effective set of policy instruments to achieve an efficient interest rate transmission. For instance, as suggested in Acharya et al. (2012), the presence of liquidity abundant financial institutions with market power could support central bank's virtuous role in the efficiency and stability of the interbank market as credible provider of liquidity to a broad spectrum of financial institutions. Also, characterizing the actual topology of interbank funds networks is essential for policymakers because of the relation between their structures and their resilience, robustness, contagion, and efficiency (see Memmel and Sachs (2013)). In our context, the existence of super-spreaders that provide efficient liquidity short-cuts between financial institutions may alleviate the inefficiencies resulting from the under-provision of liquidity cross-insurance in interbank markets (see Castiglionesi and Wagner (2013)).

This paper proposes an alternative approach to the analysis of the interbank funds market and its role for monetary policy transmission and financial stability. The suggested approach consists of using network analysis and an information retrieval algorithm for studying the connective and hierarchical structure of the Colombian interbank funds market. As suggested by Georg and Poschmann (2010), our approach includes central bank's monetary policy transactions (i.e. open market operations via repos) in the interbank funds network. Hence, based on a unique dataset, our approach enhances the scope of the traditional network analysis on interbank data. We model interbank market participants' linkages and identify how the liquidity provided by the central bank is allocated throughout the interbank market. In particular, we propose a model to identify the most important super-spreaders of the central banks liquidity in the interbank market. We employ several measures of network importance (i.e. centrality) as an alternative method to gauge lending relationships in the interbank market following recent approaches in the literature (see Craig, et al. 2015). Under our analytical framework, a financial institution may be considered a super-spreader for central bank's liquidity if it simultaneously excels at distributing liquidity to other participants (i.e. it is a good hub) and it excels at receiving liquidity from good hubs (i.e. it is a good authority), with the central bank being among the best hubs.

Our main findings come in the form of the identification of an inhomogeneous and hierarchical connective (core-periphery) structure, in which a few financial institutions fulfill the role of *super-spreaders* of central bank's liquidity within the interbank funds market; that is, we identify those financial institutions that excel as global borrowers and lenders. The main results concur with those of Inaoka et al. (2004), Soramäki et al. (2007), Fricke and Lux (2014), in't Veld and van Lelyveld (2014), and Craig and von Peter (2014) for the Japanese, U.S., Italian, Dutch and German interbank funds markets, respectively. Hence, we find further evidence against traditional assumptions of homogeneity in interbank direct contagion models (*á la* Allen and Gale, 2000), whereas the similarities across different interbank funds markets' topology support what Fricke and Lux (2014) allege *might be classified as a new "stylized fact" of modern interbank networks*.

Our research work contributes with new tools to examine and understand the structure and dynamics of interbank funds' networks. The resulting insights are important for the implementation of monetary policy and safeguarding financial stability. One the one hand, we find evidence supporting the key role of some financial institutions as super-spreaders of the central bank's liquidity, which improves the implementation of monetary policy. On the other hand, testing that the probability of being a super-spreader in the Colombian case is determined by financial institutions' size further supports some of the most salient findings of interbank relationships literature, as those reported in Cocco et al. (2009), Afonso et al. (2013), Fecht et al. (2011). That is, lending relationships are motivated by too-big-to-fail implicit guarantees. Thus, the larger the bank is, the more interconnected and central it is in the interbank network. This result implies greater concentration in the network of financial connections that can amplify contagion effects (see Gai and Kapadia (2010); Battiston et al. (2012)). Also, based on our tests, leverage and lending concentration are good determinants of the likelihood of being a super-spreader.

This paper is organized in five sections. The second presents the review of existing related literature. The third section introduces the methodological approach, and presents the dataset and its main topological features from the network analysis perspective. The fourth section presents the main results. The fifth presents a random effects probit regression model that explores the determinants of the probability of being a super-spreader in the Colombian interbank funds market, and the sixth section concludes.

2.2. Literature review

The recent GFC evidenced a significant reduction in the intermediation of funds in the interbank market in most industrialized economies. In the case of the U.S., the fragile liquidity conditions forced the Federal Reserve (Fed) into a rapid reduction of its policy rate, and to implement several unconventional measures to bring liquidity directly to the money market primary dealers (i.e. the group of financial institutions that help the Fed implement monetary policy) in order to assure the intermediation of funds among financial institutions. However, instead of serving as liquidity conduits, primary dealers avoided counterparty risk and hoarded, thus aggravating the adverse liquidity conditions (Gale and Yorulmazer, 2013; Afonso et al. 2011).[1] Beltran et al. (2015) document that many small lenders began reducing their lending to larger

[1] Avoiding counterparty risk and hoarding are unrelated (Gale and Yorulmazer, 2013). In the first case not supplying liquidity to other financial institutions follows concerns on the credit quality of its counterparties, whereas hoarding is due to concerns on its own access to liquidity in the future.

institutions in the core of the network starting in mid-2007. But an abrupt change occurred in the fall of 2008, when small lenders left the federal funds market *en masse*, and those that remained lent smaller amounts. They find that this behavior is associated with concerns on counterparty and liquidity risk among participants of the interbank market. Accordingly, the Fed had to implement additional measures to grant liquidity to other participants of the interbank funds market and to participants of other markets as well (see Fleming (2012); Campbell et al. (2011); Christensen et al. (2009); Duygan-Bump et al. (2013)). A similar strategy was implemented by most central banks from industrialized economies. In spite of the liquidity facilities partially alleviated tensions in the financial markets evidence suggests that the interbank market is extremely sensible to liquidity shocks.

One of the main lessons from the GFC is that policy makers have to properly identify the role of the key players in the interbank funds markets. As stated by Yellen (2013), "more-complex network structures are likely to be more opaque than less complex ones. For example, as the number of intermediaries standing between borrowers and lenders grows, it becomes increasingly difficult to understand how one member of the network fits into the overall system". Thus, these financial institutions may be considered the driving forces behind the supply and demand for funds in the interbank market, i.e. the liquidity super-spreaders.

However, not only super-spreaders may be regarded as those contributing to liquidity transmission the most, but also as those that may distort the distribution of central banks' liquidity the greatest, as was the case of primary dealers in the U.S. interbank funds market during the GFC of 2008 or of credit institutions in the Colombian money market in 2002. The Central Bank of Colombia faced a similar stance back in 2002. By mid-2002 a regional market crisis triggered by political stress in Brazil led to the disruption of external credit lines and to a sudden stop that weakened the liquidity position of financial institutions, particularly that of brokerage firms (Vargas and Varela, 2008). These financial institutions were confronted with local credit institutions' reluctance to supply liquidity amidst volatile and uncertain market conditions; as was the case during the GFC, by mid-2002 Colombian credit institutions (i.e. banking firms) with access to central bank's liquidity feared counterparty risk and hoarded. Under these circumstances, the Central Bank decided to move up its standing purchases of local sovereign securities (i.e. TES – Títulos de Tesorería) on the secondary market and to authorize brokerage firms and investment funds to conduct temporary expansion operations with the central bank (BDBR, 2003). Thus, after August 2002 credit institutions, brokerage firms and trust companies have been allowed to access central bank's temporary monetary expansion operations (e.g. open market operations via repos) in the Colombian financial market

As documented by Acharya et al. (2012), the GFC provides evidence on how banks with excess liquidity in the interbank markets (i.e. *surplus banks*) exerted their market power by rationing liquidity to financial institutions in need of liquidity.[2] This underscores the importance of identifying super-spreaders because of their role for financial stability (drivers of contagion risk) and for monetary policy transmission (conduits of central bank money).

Several studies on the topology of interbank funds market networks had been conducted, mainly to identify their properties, such as Inaoka et al. (2004) for Japan (BoJ-NET); Bech and Atalay (2010) and Soramäki et al. (2007) for the U.S. (Fedwire); Boss et al. (2004) for Austria; in't Veld and van Lelyveld (2014) and Pröpper et al. (2008) for the Netherlands; Craig and von Peter (2014) for Germany; Fricke and Lux (2014) for Italy; Cajueiro and Tabak (2008) and Tabak et al. (2013) for Brazil; and Martínez-Jaramillo et al. (2012) for Mexico.[3] Some of these studies also implement network metrics (e.g. centrality) for analytical purposes related to financial stability and contagion. Only Boss et al. (2004) includes the central bank as a participant in the interbank funds' network, but does not address its particular role. Similarly, Craig et al. (2015) find that when the network position of the bank is taken into account, central lenders in the money market bid more aggressively in the central bank' auctions. They match the data from the ECB repo auctions with the interbank market operations, but they do not incorporate how the liquidity obtained from the central bank is allocated in the interbank network.

In order to identify the topology of the Colombian interbank funds network, our model implements standard network analysis' metrics on a network resulting from merging the

[2] Acharya et al. (2012) document how the market power of J.P. Morgan may have resulted in the liquidity rationing that affected non-depositary institutions as Bear Sterns amid the GFC. Likewise, Acharya et al. also report that liquidity rationing by super-spreaders may have occurred in several episodes before the GFC, such as the collapse of Long-Term Capital Management in 1998 and of Amaranth Advisors in 2006.

[3] There are few studies worth mentioning in the Colombian case. Cardozo et al. (2011) and González et al. (2013) describe the functioning of the local money market. Estrada and Morales (2008) and Capera-Romero et al. (2013) study the link between the local interbank funds market structure and financial stability; however, both studies' quantitative and analytical results are limited by their choice of datasets.

Colombian interbank funds market and the central bank's open market operations. That is, we merge two networks, one comprising non-collateralized lending among financial institutions at all available maturities (i.e. intraday, overnight, term lending), the other containing central bank's lending by means of repos. Unlike most literature, our networks are observed, and no Furfine-type algorithm is required for their construction.

Afterwards, we introduce an information retrieval algorithm to estimate *authority centrality* and *hub centrality* (Kleinberg, 1998), and to identify interbank funds market's super-spreaders. Under our analytical framework a financial institution may be considered a super-spreader for central bank's liquidity if it simultaneously excels at distributing liquidity to other participants (i.e. it is a good hub) and it excels at receiving liquidity from good hubs (i.e. it is a good authority), with the central bank being among the best hubs. To the best of our knowledge, implementing an information retrieval algorithm for identifying super-spreaders in an interbank network that comprises central bank's liquidity provision has not been documented in related literature.

The closest research work is that of Craig and von Peter (2014), Fricke and Lux (2014), and in't Veld and van Lelyveld (2014), who document the existence of core-periphery structures in the German, Italian and Dutch interbank funds markets, respectively. Such tiered hierarchical structure not only concurs with our results, but also verifies the importance of a limited number of financial institutions for the transmission of liquidity within the money market; in this sense, the so-called *top-tier* or *money center banks* of Craig and von Peter (2014) are analogous to our liquidity super-spreaders. However, because their main objective is different from ours, none of those articles include the direct liquidity provision by the central bank in their models, nor do they implement network analysis metrics and an information retrieval algorithm to pinpoint liquidity super-spreaders. Therefore, our work makes a contribution to the identification of central bank's liquidity super-spreaders in interbank funds.

Identifying central bank's money super-spreaders is not only critical for the implementation of monetary policy, but it also coincides with the *robust-yet-fragile* characterization of financial networks by Haldane (2009). This characterization poses major challenges from the financial stability perspective, including the revision of traditional interbank contagion models of Allen and Gale (2000) and of most interbank direct contagion models that followed (e.g. Cifuentes et al. (2005); Gai and Kapadia (2010); Battiston et al. (2012)).

Our results concur with recent literature on the inhomogeneous and core-periphery features of interbank funds networks, and further support that these are stylized facts of interbank funds markets, as claimed by Fricke and Lux (2014). Moreover, an overlooked feature common to the U.S., Austrian, Dutch and Colombian interbank funds market is revealed: they are *ultra-small* networks in the sense of Cohen and Havlin (2003). This feature is consistent with the existence of a core that provides an efficient short-cut for most peripheral participants in the network, and points out that the structure of these interbank funds networks favors an efficient spread of liquidity, but also of contagion effects.

As tested by Craig and von Peter (2014) for the German interbank market, the probability of being a super-spreader in the Colombian case is determined by financial institutions' size. This result is robust and overlaps with alternative measures of importance (i.e. centrality) within the interbank funds network. Accordingly, concurrent with literature on lending relationships in interbank markets (Cocco et al. (2009); Afonso et al. (2013)), size may be the main factor behind the interbank funds connective and hierarchical architecture. In this sense, we provide evidence that financial institutions do not connect to each other randomly, but they interact based on a size-related preferential attachment process, presumably driven by too-big-to-fail implicit subsidies or market power. Also, we find evidence of leverage and lending concentration as good determinants of the likelihood of being a super-spreader.

2.3. Methodological approach

Three methodological steps are necessary for assessing financial institutions' central bank liquidity spreading capabilities in the local interbank funds market. First, the corresponding network merging interbank funds and monetary policy transactions has to be built from available data. Second, network analysis' basic statistics have to estimated and interpreted. Third, appropriate metrics for assessing the spreading capabilities of financial institutions have to be chosen. These three steps are introduced next.

2.3.1. The interbank funds and central bank's repo network

Data from the local large-value payment system (CUD – *Cuentas de Depósito*) was used to filter two types of transactions: interbank funds and central bank's repos. We use quarterly data from 2010 to 2013. Unlike most literature on interbank networks, the Colombian large-value payment system allows for identifying transactions in a direct manner, thus no Furfine-type algorithm for inferring transactions is required. [4]

In the Colombian case the interbank funds market is not limited to credit institutions. As defined by local regulation, it corresponds to funds *provided (acquired) by a financial institution to (from) other financial institution without any agreement to transfer investments or credit portfolios*; this is, the interbank funds market consists of all non-collateralized borrowing/lending between all types of financial institutions. For comprehensiveness, we work with all maturities available in the interbank funds market, namely intraday, overnight, and term lending.[5]

The interbank funds market is the second contributor to the exchange of liquidity between financial institutions in the Colombian money market. As of 2013, the interbank funds market represents about 15.4% of financial institutions' exchange of liquidity, below sell/buy backs on sovereign local securities (84.4%), but above repos between financial institutions (0.2%).[6] Despite the fact that the use of sell/buy backs between financial institutions exceeds that of the interbank funds market, analyzing the former for monetary purposes may be inconvenient because its interest rate may be affected by the presence of securities-demanding financial institutions (instead of cash-demanding), and by the absence of mobility restrictions on

[4] The database was extracted from the large-value payment system (CUD) by means of filtering the corresponding transaction codes; the Colombian Central Bank (i.e. the owner and operator of CUD) assigns transaction codes, and financial institutions and financial infrastructures are obliged to use them to report their transactions.

[5] It is important to mention that there is no direct interconnection with other unsecured interbank markets in the region. Banks' interaction with banks in other jurisdictions takes place via cross-border lending market, which is a credit market used for term loans and credit lines with maturities between 3 months to 5 years.

[6] Only sell/buy backs and repos with sovereign local securities as collateral are considered. Sovereign local securities acting as collaterals for borrowing between financial institutions in the money market usually account for about 80% of the total; if repos with the central bank are included, sovereign local securities represent about 90% of all collateralized liquidity sources.

collateral (Cardozo et al. 2011). Hence, as the interbank funds market is the focus of central bank's implementation of monetary policy (Allen et al. 2009), it is also the focus of our analysis.

Central bank's repos correspond to the liquidity granted to financial institutions on behalf of monetary policy considerations by means of standard open market operations, in which the eligible collateral is mainly local sovereign securities. Access to liquidity by means of central bank's repos is open to different types of financial institutions (i.e. banking and non-banking), but is limited to those that fulfill some financial and legal prerequisites. For instance, as of December 2013, 87 financial institutions were eligible for taking part in central bank's repo auctions: 42 credit institutions (CIs), 20 investment funds (IFs), 18 brokerage firms (BKs), 4 pension funds (PFs) and 3 other financial institutions (Xs). As of 2013, the value of Colombian central bank's repo facilities was about six times that of interbank funds transactions.

Merging the interbank funds market and the central bank's repos into a single network follows several reasons. First, by construction, the central bank is the most important participant of the interbank funds market, in which its intervention determines the efficient allocation of money among financial institutions, as underscored by Allen et al. (2009) and Freixas et al. (2011). Second, as in Acharya et al. (2012), the liquidity provision by the central bank is an important factor that may improve the private allocation of liquidity among banks in presence of frictions in the interbank market (i.e. market power by surplus banks). Third, merging both networks allows for comprehensively assessing how central bank's liquidity spreads across financial institutions in the interbank funds market; therefore, as in Georg and Poschmann (2010; p.2), *a realistic model of interbank markets has to take the central bank into account*. Fourth, as the access to central bank's repos is open to all types of financial institutions, identifying which institutions effectively access the central bank's open market operations facilities and excel as distributors of liquidity may provide useful information for designing liquidity facilities and implementing monetary policy.

Accordingly, based on data corresponding to the fourth quarter 2013, **Figure 1** displays the actual network resulting from merging the interbank funds market and the central bank's repo facilities. The direction of the arrow or arc corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. Only the original transaction (i.e. from the lender to the borrower) is considered; transactions consisting of borrowers paying back for interbank or repo funds are omitted, as are intraday (i.e. non-monetary) repos.

Some salient features of **Figure 1** are worth mentioning. First, due to the open (i.e. non-tiered) access to central bank's liquidity, all types of financial institutions are connected to the central bank via repos. Second, the widest links correspond to funds from the central bank to some credit institutions, which corresponds to the role of the central bank as liquidity provider within 2013's expansionary monetary policy framework. Third, there is a noticeable concentration of interbank links in credit institutions receiving funds from the central bank; the estimated correlation coefficient (0.75) provides evidence of the linear dependence between the liquidity granted by the central bank via repos to financial institutions and their number of links during 2013. Fourth, most weakly connected institutions correspond to non-credit institutions.

2.3.2. Network analysis

A network, or graph, represents patterns of connections between the parts of a system. The most common representation of a network is the *adjacency matrix*. In the case of a directed network or *digraph*, in which the direction of the connection is meaningful (i.e. no reciprocity is guaranteed), let n represent the number of vertexes or participants, the adjacency matrix A is a square matrix of dimensions $n \times n$ with elements A_{ij} such that

$$A_{ij} = \begin{Bmatrix} 1 \text{ if there is an edge from } i \text{ to } j, \\ 0 \text{ otherwise.} \end{Bmatrix} \tag{1}$$

It may be useful to assign real numbers to the edges. These numbers may represent distance, frequency or value, in what is called a weighted network and its corresponding weighted adjacency matrix (W_{ij}). For a financial network, the weights could be the monetary value of the transaction or of the exposure.

Regarding the characteristics of the system and its elements, a set of concepts is commonly used. The simplest concept is the vertex *degree* (k_i), which corresponds to the number of edges connected to it. In directed graphs, where the adjacency matrix is non-symmetrical, *in degree*

($\mathcal{k}_i^{in}$) and *out degree* ($\mathcal{k}_i^{out}$) quantifies the number of incoming and outgoing edges, respectively (see **Table 2.A4**). In the weighted graph case the degree may be informative, yet inadequate for analyzing the network. *Strength* ($\mathcal{s}_i$) measures the total weight of connections for a given vertex, which provides an assessment of the intensity of the interaction between participants. *In strength* ($\mathcal{s}_i^{in}$) and *out strength* ($\mathcal{s}_i^{out}$) sum the weight of incoming and outgoing edges, respectively.

Some metrics enable us to determine the connective pattern of the graph. The simplest metric for approximating the connective pattern is *density* ($\mathcal{d}$), which measures the cohesion of the network. The *density* of a graph with no self-edges is the ratio of the number of actual edges ($\mathcal{m}$) to the maximum possible number of edges (see **Table 2.A4**). By construction, density is restricted to the $0 < \mathcal{d} \leq 1$ range. Networks are commonly labeled as sparse when the density is much smaller than the upper limit ($\mathcal{d} \ll 1$), and as dense when the density approximates the upper limit ($\mathcal{d} \cong 1$).

An informative alternative measure for density is the degree probability distribution ($\mathcal{P}_{\mathcal{k}}$). This distribution provides a natural summary of the connectivity in the graph (Kolaczyk, 2009). Akin to density, the first moment of the distribution of degree ($\mu_{\mathcal{k}}$) measures the cohesion of the network, and is usually restricted to the $0 < \mu_{\mathcal{k}} < n - 1$ range. A sparse graph has an average degree that is much smaller than the size of the graph ($\mu_{\mathcal{k}} \ll n - 1$).

Most real-world networks display right-skewed distributions, in which the majority of vertexes are of very low degree, and few vertexes are of very high degree, hence the network is inhomogeneous. Such right-skewness of degree distributions of real-world networks has been documented to approximate a power-law distribution (Barabási and Albert, 1999). In traditional random networks, in contrast, all vertexes have approximately the same number of edges.[7] The power-law (or Pareto-law) distribution suggests that the probability of observing

[7] Random networks correspond to those originally studied by Erdös and Rényi (1960), in which connections are homogeneously distributed between participants due to the assumption of exponentially decaying tail processes for the distribution of links –such as the Poisson distribution. This type of network, also labeled as "random" or "Poisson", was –explicitly or implicitly- the main assumption of most literature on networks before the seminal work of Barabási and Albert (1999) on scale-free networks.

a vertex with k edges obeys the potential functional form in (2), where z is an arbitrary constant, and γ is known as the *exponent* of the power-law.

$$\mathcal{P}_k \propto z k^{-\gamma} \tag{2}$$

Besides degree distributions approximating a power-law, other features have been identified as characteristic of real-world networks: (i) low mean geodesic distances; (ii) high clustering coefficients; and (iii) significant degree correlation, which we explain next.

Let g_{ij} be the *geodesic distance* (i.e. the shortest path in terms of number of edges) from vertex i to j. The mean geodesic distance for vertex i (ℓ_i) corresponds to the mean of g_{ij}, averaged over all reachable vertexes j in the network (Newman, 2010), as in **Table 2.A4**. Respectively, the mean geodesic distance or average path length of a network (i.e. for all pairs of vertexes) is denoted as ℓ (without the subscript), and corresponds to the mean of ℓ_i over all vertexes. Consequently, the mean geodesic distance (ℓ) reflects the global structure; it measures how big the network is, it depends on the way the entire network is connected, and cannot be inferred from any local measurement (Strogatz, 2003).

The mean geodesic distance (ℓ) of random or Poisson networks is small, and increases slowly with the size of the network; therefore, as stressed by Albert and Barabási (2002), random graphs are small-world because in spite of their often large size, in most networks there is relatively a short path between any two vertexes. For random networks: $\ell \sim \ln n$ (Newman et al. 2006). This slow logarithmic increase with the size of the network coincides with the small-world effect (i.e. short average path lengths).

However, the mean geodesic distance for scale-free networks is smaller than $\ell \sim \ln n$. As reported by Cohen and Havlin (2003), scale-free networks with $2 < \gamma < 3$ tend to have a mean geodesic distance that behaves as $\ell \sim \ln\ln n$, whereas networks with $\gamma = 3$ yield $\ell \sim \ln n / (\ln \ln n)$, and $\ell \sim \ln n$ when $\gamma > 3$. For that reason, Cohen and Havlin (2003) state that scale-free networks can be regarded as a generalization of random networks with respect to the mean average geodesic distance, in which scale-free networks with $2 < \gamma < 3$ are "ultra-small".

Table 2.1 presents the average statistics estimated for the interbank funds and central bank's repo network, estimated on the 16 quarters in the sample. **Figure 2.A4** exhibits the evolution of these statistics throughout the period. Evidence advocates that the network is (i) sparse, with low density resulting from the number of observed links being much smaller than the potential number of links, and with an average degree (i.e. mean of links per institution) much smaller than the number of participants; (ii) ultra-small in the sense of Cohen and Havlin (2003), in which the average minimal number of links required to connect any two financial institutions (i.e. the mean geodesic distance) is particularly low (i.e. ~2) with respect to the number of participants; (iii) inhomogeneous, in which the dispersion, asymmetry, kurtosis and the order of the power-law exponent for the distribution of links and their monetary values suggest the presence of a few financial institutions that are heavily connected and large contributors to the system, whereas most institutions are weakly connected and minor contributors, with the distribution of degree and strength presumably approximating a scale-free distribution;[8] (v) *assortative mixing by degree*, which means that heavily (weakly) connected financial institutions tend to be connected with other heavily (weakly) connected, especially for the in-degree case.

Altogether, these features concur with the scale-free and assortative mixing by degree connective structure of social networks reported by Newman (2010), and suggest the presence of a structure similar to a core-periphery within the network under analysis. Moreover, as the interbank funds network is ultra-small in the sense of Cohen and Havlin (2003), with participants being one financial institution away from the others, the process of liquidity spreading within the interbank funds network is highly efficient; likewise, contagion spreads within the network with ease. Most of these main features are robust to the exclusion of the central bank, and tend to be consistent throughout the quarters under analysis (see **Figure 2.A4**).

A remarkable but overlooked feature in **Table 2.1** is worth noting. A mean geodesic distance around 2 not only agrees with ultra-small networks (Cohen and Havlin, 2003), but also suggests

[8] The estimation of the power-law exponent was based on the maximum likelihood method proposed by Clauset et al. (2009); this method is preferred to the traditional ordinary least-squares due to documented issues regarding the latter (as in Clauset et al. 2009, Stumpf and Porter, 2012). The power-law distribution of links is an asymptotic property, thus a strict match between observed and expected theoretical properties for determining the scale-free properties of non-large networks may be impractical.

that the bulk of financial institutions require about two links (i.e. circa one financial institution in-between) to connect to any other financial institution in the interbank funds network, meaning that the core provides an efficient short-cut for most peripheral participants in the network; again, the spreading capabilities of the network are particularly high. Interestingly, mean geodesic distances reported by Boss et al. (2004), Soramäki et al. (2007), Bech and Atalay (2010), and Pröpper et al. (2008), for the Austrian, U.S. and Dutch interbank funds networks are about 2, consistent with ultra-small networks and with the role of a core providing an effective short-cut for the network; likewise, mean geodesic distances reported by León and Berndsen (2014) for the Colombian large-value payment system (CUD) and the main local sovereign securities settlement system (DCV – *Depósito Central de Valores*) are also about 2.

All in all, these findings concur with those of Craig and von Peter (2014) about the presence of tiering in the interbank funds market in the German banking system, and with the corresponding *money center banks*. Moreover, as also highlighted by Craig and von Peter (2014), these features verify that the connective structure of financial networks departs from traditional assumptions of homogeneity and representative agents (as in Allen and Gale (2000); Freixas et al. (2000); Cifuentes et al. (2005); Gai and Kapadia (2010)), and further supports the need to achieve the main goal of this paper: identifying which financial institutions are particularly relevant for the network.

2.3.3. Identifying super-spreaders in financial networks

Whenever financial networks' observed connectedness structure is inhomogeneous the underlying system's fragility issue arises. In those networks the extraction or failure of a participant will have significantly different outcomes depending on how the participant is selected. When randomly selected, the effect will be negligible, and the network may withstand the removal of several randomly selected participants without significant structural changes. However, if selected because of their high connectivity, extracting a small number of participants may significantly affect the network's structure. In this sense, a rising amount of financial literature is encouraging the usage of network metrics of importance (e.g. centrality) for identifying super-spreaders (Markose et al. (2012); Markose (2012); León et al. (2012); Haldane and May (2011); Haldane (2009)).

Most literature on financial super-spreaders seeks to identify those institutions that may lead contagion effects due to their network connectivity, *high-infection individuals* (Haldane, 2009), or those that *dominate in terms of network centrality and connectivity* (Markose et al. 2012). Despite the traditional negative connotation of super-spreaders in financial networks, in the present case the super-spreader financial institution is considered a good conduit for monetary policy as well.

There are many approaches for assessing the importance of individuals or institutions within a network. However, centrality is the most common concept, with many definitions and measures available. The simplest measures are related to local metrics of centrality, such as degree (i.e. number of links, $\mathcal{k}_i$) or strength (i.e. weight of links, $\mathcal{s}_i$), but they fall short to take into account the global properties of the network; this is, the centrality of the counterparties is not taken into account as a source of centrality. Moreover, they do not capture the in-between or intermediation role of vertexes.

An alternative to degree and strength centrality is betweenness centrality ($\mathcal{b}_i$). As presented in **Table 2.A4**, it measures the extent to which a vertex lies on paths of other vertexes (Newman, 2010). It is based on the role of the i-vertex in the geodesic (i.e. the shortest) path between two other (p and q) vertexes ($\mathcal{g}_{pq}$). In the case at hand, betweenness centrality is appealing. A central intermediary in the interbank funds market should fulfill an in-between role for the network: it should stand in the interbank funds' path of other financial institutions. Yet, as it is a path-dependent centrality measure, it does not consider linkages' intensity or value, and it does not consider the centrality of adjacent vertexes as a source of centrality.

The simplest global and non-path-based measure of centrality is eigenvector centrality, whereby the centrality of a vertex is proportional to the sum of the centrality of its adjacent vertexes; accordingly, the centrality of a vertex is the weighted sum of centrality at all possible order adjacencies. Hence, in this case centrality arises from (i) being connected to many vertexes; (ii) being connected to central vertexes; (iii) or both.[9] Alternatively, as put forward by

[9] For instance, Markose et al. (2012) use eigenvector centrality to determine the most dominant financial institutions in the U.S. credit default swap market, and to design a super-spreader tax that mitigates potential socialized losses.

Soramäki and Cook (2012), eigenvector centrality may be thought of as the proportion of time spent visiting each participant in an infinite random walk through the network.

Eigenvector centrality is based on the *spectral decomposition* of a matrix. Let Ω be an adjacency matrix (weighted or non-weighted), Λ a diagonal matrix containing the eigenvalues of Ω, and Γ an orthogonal matrix satisfying $\Gamma\Gamma' = \Gamma\Gamma = \mathrm{I}_n$, whose columns are eigenvectors of Ω, such that

$$\Omega = \Gamma\Lambda\Gamma' \tag{3}$$

If the diagonal matrix of eigenvalues (Λ) is ordered so that $\lambda_1 \geq \lambda_2 \cdots \lambda_n$, the first column in Γ corresponds to the principal eigenvector of Ω. The principal eigenvector (Γ_1) may be considered as the leading vector of the system, the one that is able to explain the most of the underlying system, in which the positive n-scaled scores corresponding to each element may be considered as their weights within an index.

Because the largest eigenvalue and its corresponding eigenvector provide the highest accuracy (i.e. explanatory power) for reproducing the original matrix and capturing the main features of networks (see Straffin, 1980), Bonacich (1972) envisaged Γ_1 as a global measure of popularity or centrality within a social network.

However, eigenvector centrality has some drawbacks. As stated by Bonacich (1972), eigenvector centrality works for symmetric structures only (i.e. undirected graphs); however, it is possible to work with the right (or left) eigenvector (as in Markose et al. 2012), but this may entail some information loss. Yet, the most severe inconvenience from estimating eigenvector centrality on asymmetric matrices arises from vertexes with only outgoing or incoming edges, which will always result in zero eigenvector centrality, and may cause some other non-strongly connected vertexes to have zero eigenvector centrality as well (Newman, 2010). In the case of acyclic graphs, such as financial market infrastructures' networks (León and Pérez, 2014), this may turn eigenvector centrality useless; this is also our case because the central bank has no incoming links, and because some peripheral financial institutions are weakly connected.

Among some alternatives to surmount the drawbacks of eigenvector centrality (e.g. PageRank, Katz centrality), the HITS (Hypertext Induced Topic Search) information retrieval algorithm by

Kleinberg (1998) is convenient for several reasons. There are four main advantages in our case: (i) unlike eigenvector centrality, it is designed for directed networks, in which the adjacency matrix may be non-symmetrical; (ii) it provides two separate centrality measures, *authority centrality* and *hub centrality*, which correspond to the eigenvector centrality as recipient and as originator of links, respectively; (iii) when dealing with weakly connected vertexes, it avoids introducing stochastic or arbitrary adjustments (as in PageRank and Katz centrality) that may be undesirable from an analytical point of view, and (iv) because the authority (hub) centrality of each vertex is defined to be proportional to the sum of the hub (authority) centrality of the vertexes that point to it (it points to), the importance of vertexes fulfilling an in-between role for the network tends to be captured.[10]

The estimation of authority centrality ($\mathcal{a}_i$) and hub centrality ($\hbar_i$) results from estimating standard eigenvector centrality (3) on two modified versions of the weighted adjacency matrix, $\mathcal{A}$ and $\mathcal{H}$ (4).

$$\mathcal{A} = \Omega^T\Omega \qquad\qquad \mathcal{H} = \Omega\Omega^T \tag{4}$$

Multiplying the adjacency matrix with a transposed version of itself allows identifying directed (*in* or *out*) second order adjacencies. Regarding $\mathcal{A}$, multiplying $\Omega^T$with Ω sends weights backwards –against the arrows, towards the pointing vertex-, whereas multiplying Ω with Ω^T (as in $\mathcal{H}$) sends scores forwards –with the arrows, towards the pointed-to vertex (Bjelland et al. 2008). Thus, the HITS algorithm works on a circular thesis: the authority centrality ($\mathcal{a}_i$) of each participant is defined to be proportional to the sum of the hub centrality ($\hbar_i$) of the participants that point to it, and the hub centrality of each participant is defined to be proportional to the sum of the authority centrality of the participant it points-to.

The circularity of the HITS algorithm is most convenient for identifying super-spreaders of central bank's liquidity. An institution may be considered a good conduit for central bank's liquidity if it simultaneously is a good hub (i.e. it excels at distributing liquidity within the interbank funds market) and a good authority (i.e. it excels at receiving liquidity from good

[10] The relevance of the in-between role of a vertex has an inverse relation with the existence of other vertexes providing the same connective role. Thus, a vertex being the sole provider of a connective role will concentrate all the weighted average centrality of the vertexes it connects. Thus, in this sense, the HITS algorithm captures the in-between role of vertexes.

hubs, with the central bank being among the best hubs). On the other hand, if an institution is a good authority but a meager hub it may be regarded as a poor conduit for central bank's liquidity; likewise, if an institution is a good hub but a modest authority its central bank's liquidity transmission capabilities may be regarded as low.

The eigenvector centrality framework behind the estimation of authority centrality and hub centrality allows both metrics to capture the impact of liquidity on a global scale. Accordingly, all financial institutions that are connected to the central bank and the most important hubs, either directly or indirectly, inherit some degree of authority centrality depending on the intensity of the links to those providers of liquidity. Likewise, all financial institutions that distribute liquidity in the system inherit some degree of hub centrality depending on the intensity of the links to all those receiving liquidity.

In this sense, an institution simultaneously displaying a high score in both authority (a_i) and hub centrality ($\hbar_i$) is expected to be a dominant participant in the transmission of funds from the central bank to the interbank funds market and within the interbank funds market. Therefore, the liquidity spreading index of an i-financial institution (LSI_i) corresponds to the product of both normalized centrality measures, as in (5). The choice of the product operator is consistent with the aim of identifying institutions that simultaneously are a good hub and a good authority.[11]

$$LSI_i = \frac{\left(\frac{a_i}{\sum_{i=1}^{n} a_i} \times \frac{\hbar_i}{\sum_{i=1}^{n} \hbar_i}\right)}{\sum_{i=1}^{n}\left(\frac{a_i}{\sum_{i=1}^{n} a_i} \times \frac{\hbar_i}{\sum_{i=1}^{n} \hbar_i}\right)} \tag{5}$$

Where, by construction

$$0 \leq LSI_i \leq 1$$

And

[11] Other conjunction operators may be chosen, such as $min(\cdot)$. Using the average of hub centrality and authority centrality is feasible, but may fail to discard institutions that are good authorities but mediocre hubs, and vice versa.

$$LSI = \sum_{i=1}^{n} LSI_i = 1$$

Since LSI_i is a measure of the contribution of an individual financial institution to the product of all financial institutions' hub and authority centrality, super-spreaders may be defined as those contributing the most to LSI. Super-spreaders are those financial institutions that simultaneously excel as global borrowers and lenders of central bank's money in the interbank funds network. To the best of our knowledge, this is the first attempt to use a global and non-path dependent centrality measure to identify super-spreaders in an interbank network comprising the central bank.

2.4. Main results

We evaluated the 2010Q1-2013Q4 period, in which the stance of the monetary policy had cycles of tightening and easing of the liquidity conditions. This period allows to evaluate the behavior of interbank market' participants under regular stances of the monetary policy. Based on the methodological approach described in the previous section, the 16-quarter average liquidity-spreading index (LSI_i) was estimated on the corresponding interbank funds and central bank's repo networks. **Figure 2** presents the top-15 financial institutions by their estimated LSI_i.[12]

The top-15 financial institutions by average LSI are credit institutions (CIs), which together contribute with 93.91% of LSI. The concentration in the top-ranked financial institutions is clear, with the first (CI3) contributing with about 25% of the LSI, and the top-five (CI3, CI22, CI1, CI23, C20) contributing with about 75%. Hence, results suggest that CIs provide the main conduit for central bank's liquidity within the Colombian financial system.

Figure 3 displays how liquidity spreads from the central bank throughout the interbank funds market in the last quarter of 2013; **Figure 2.A5** exhibits the network for each quarter in the sample. Again, the direction of the arrow or arc corresponds to the direction of the funds

[12] The central bank's LSI_i is neither reported, nor analyzed. After estimating LSI_i the central bank's score is excluded, and the remaining scores are standardized accordingly. This follows our focus on identifying super-spreader financial institutions different from the central bank. The same procedure applies for other centrality measures here implemented.

transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. The size of the vertexes corresponds to the contribution to LSI in the corresponding period. The central bank, and the top-5 financial institutions by LSI_i for this quarter (i.e. CI22, CI20, CI3, CI1, CI5) are tagged for illustrative purposes.

It is noticeable that those financial institutions that display larger vertexes are credit institutions only. Although all types of financial institutions receive liquidity from the central bank, it is evident that only a few credit institutions concentrate most of open market operations borrowing. It is also clear that some credit institutions (e.g. CI22) fulfill an intermediary role for several other financial institutions, whereas intermediation by non-credit institutions appears to be absent.

Figure 4 displays the graph corresponding to interbank funds transactions between institutions that contribute the 99th percentile of the LSI in the last quarter of 2013; that is, the supers-spreaders of central bank liquidity. Again, the direction of the arrow or arc corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the value of transactions within this 10-credit institution core. The size of the vertexes corresponds to the contribution to LSI in the corresponding period.

As expected from **Figures 2** and **Figure 3**, all financial institutions in **Figure 4** all are credit institutions. Also, as expected from the core in a core-periphery hierarchical structure, these ten credit institutions constitute a particularly dense network, in which almost all vertexes connect to each other (i.e. 94.44% of the potential connections are observed). Likewise, the mean geodesic distance is approximately 1. The sum of transactions' value within this core represents 31.86% of the interbank funds network.

Figure 5 displays the graph corresponding to interbank funds transactions occurring between financial institutions not considered in **Figure 4**; that is, those that may be considered the periphery of the network. Unlike **Figure 4**, there are all types of financial institutions. As expected from the periphery in a core-periphery structure, most of them do not connect to each other, degree and strength is unevenly distributed, and the network is particularly sparse (i.e. 1.26% of the potential connections are observed). And most interbank funds transactions and their value are among credit institutions; transactions involving non-credit institutions are rare, which means that most of them connect to credit institutions in the core only.

The sum of transactions' value within this periphery network represents 16.70% of the whole interbank funds network, whereas transactions between the core and the periphery represent about 51.44%. Such preference of peripheral financial institutions to maintain relationships with the core overlaps with evidence reported by Cocco et al. (2009), Fricke and Lux (2014) and Craig and von Peter (2014) and Craig et al. (2015).

2.4.1. What makes a super-spreader in the Colombian interbank funds market?

The size of institutions in financial markets is known to be inhomogeneous, with a few that may be regarded as "too-large" and many "too-small", presumably approximating a power-law distribution (Gabaix et al. (2003); Fiaschi et al. (2013)), even in the Colombian case (León, 2014). Craig and von Peter (2014), Fricke and Lux (2014), in't Veld and van Lelyveld (2014), and Cajueiro and Tabak (2008) confirm that there is a significant relation between financial institutions' size and their position in the interbank funds' hierarchy in the respective German, Italian, Dutch, and Brazilian interbank markets. In these markets large banks tend to be in the core, whereas small banks are found in the periphery. This is consistent with Cocco et al. (2009), who report that size is an important determinant of interbank lending relationships, with smaller banks being less likely to act as intermediaries.

Regarding the Colombian case the relation between size and the role as super-spreader in the interbank funds market is evident. **Figure 6** exhibits the double logarithmic scale plot for Colombian financial institutions' 2013 average assets value, in which the horizontal axis corresponds to the logarithm of assets value, the vertical axis to the logarithm of the cumulative frequency for each asset value, and each circle represents a single financial institution. As also reported by Fiaschi et al. (2013) for the U.S. financial market, such double logarithmic plot exhibits an interesting feature: it is an "interrupted" plot. Such interruption, also reported for the Colombian case (León, 2014), yields two different size regimes with two different distributional forms. It verifies that in the Colombian financial market there are large (i.e. above COP 8.8 Trillion) and small (i.e. below COP 2.5 Trillion) financial institutions, and that they may be pinpointed rather objectively.

Filling (in black) the circles corresponding to the super-spreaders (i.e. financial institutions in the 99th percentile of LSI during 2013) yields an obvious observation: in the Colombian interbank funds market all super-spreaders pertain to the largest financial institutions regime (i.e. assets above COP 8.8 trillion); four large financial institutions do not classify as super-spreaders under the arbitrarily-chosen 99th percentile threshold. The average size of super-spreaders is about 33 times that of other financial institutions; this agrees with evidence reported by Craig and von Peter (2014) for the German interbank funds market (i.e. about 51 times). Therefore, two distinctive features may determine super-spreading capabilities of financial institutions in the Colombian interbank funds market, namely being a credit institution and being large.

In order to provide further evidence on the characteristics of the financial institutions that may be considered as super-spreaders, we exploit the panel data structure by implementing a random effects probit model on a set of institution-specific variables that are standard in the literature: size, leverage, financial performance, and the concentration of borrowing and lending counterparties. These variables serve as regressors in the model, in which the dependent variable (LSI_{it}) is binary according to financial institution's super-spreader features: $LSI_{it} = 1$ if it pertains to the 99th percentile (i.e. it is a super-spreader), and $LSI_{it} = 0$ otherwise.

Regarding the choice of the independent variables, not only size ($size$) is a leading determinant of the position within a core-periphery structure for the German, Italian, and Dutch interbank markets, but graphical inspection of **Figure 6** also points out the relevance of size in the Colombian case. Leverage (lev) corresponds to the traditional debt to assets ratio, which is intended to test whether super-spreaders may be predicted by the capital structure of financial institutions. Financial performance corresponds to the return over assets ratio (roa), which is intended to test whether super-spreaders may be predicted by their profitability. Finally, the borrowing concentration ($borr$) and lending concentration ($lend$) correspond to the calculation of the Herfindahl-Hirschman index (HHI) on the contribution of borrowing and lending counterparties for each financial institution, respectively. Including these two variables aim at examining whether concentrating (or diversifying) counterparties may serve to predict super-spreaders.[13]

Accordingly, based on the choice of percentile for the dataset under analysis (i.e. 99th), the probit model serves as a test of the significance of the selected institution-centric variables for predicting the membership to the super-spreader class. Let X_{it} represent the set of institution-specific variables (i.e. $size$, lev, roa, $borr$, $lend$); pr denote probability; and Φ the Cumulative Distribution Function of the standard normal distribution, the probit model is as in (6).

$$pr(LSI_{it} = 1 | X_{it}) = \Phi(X_{it}'\beta) \int_{-\infty}^{X'\beta} \emptyset(z)dz \tag{6}$$

Where

$$LSI_{it} = \begin{cases} 1 \text{ if } i \text{ is a super-spreader at time } t \\ 0 \text{ otherwise} \end{cases}$$

All independent variables are standard scores (i.e. number of standard deviations above the estimated mean) computed using quarterly information from 2010Q1 to 2013Q4. The LSI_{it} is computed for each quarter and the super-spreaders are selected at the 99th percentile. Standard descriptive statistics for the variables are presented in **Table 2.A1.**

However, because the functional form of LSI_{it} in (5) seeks to filter out those financial institutions that simultaneously display both authority centrality (a_{it}) and hub centrality ($\hbar_{it}$), the same probit regression model is implemented in two alternate models with authority and hub centrality as dependent variables. Using authority centrality and hub centrality as alternative dependent variables helps us to examine if the selected independent variables differ

[13] Financial institutions' access to central bank's liquidity –an intuitive variable- would predict super-spreaders perfectly; hence, despite its consideration in the probit model makes its estimation unfeasible, it should be considered for analytical purposes. Some institution-centric variables (e.g. equity, return over equity) were discarded due to their lack of significance or redundancy with those presented, whereas others (e.g. non-performing loans) were excluded because they are available for credit institutions only. Initial liquidity balance in central bank's accounts, cash, and proprietary investments, were discarded due to potential multicollinearity with size; the cross-correlation between the three variables is high, and asset size encompasses them all. Likewise, the value of repos with the central bank is also discarded for potential multicollinearity with size.

in their explanatory power because of the potentially distinct role of financial institutions as global receivers or distributors of liquidity. Simple local centrality measures, namely degree (i.e. number of links, $\mathscr{k}_{it}$) and strength (i.e. weight of links, $\mathscr{s}_{it}$), and betweenness centrality (i.e. role as connector between vertexes, $\mathscr{b}_{it}$) are also reported for robustness and comparison purposes. Besides, to check the robustness of the model we also estimate the probit model using 95th and 90th percentile thresholds for determining super-spreaders.

Overall, concurrent with the literature, we expect a strong and positive dependence between size and the probability of being a super-spreader. One would expect that the more leveraged a financial institution is, the cheaper its cost of capital, and consequently the cheaper the liquidity it may lend. Therefore, we expect a positive relation between leverage and the probability of being a super-spreader and a good hub, but we do not have a clear expectation on the relation with the probability of being a good authority. Moreover, as the average credit institution in the Colombian case displays leverage levels about 2.5 times that of the average non-credit institution, we expect a positive and significant relation between leverage and super-spreaders. Regarding financial performance, as larger banks are reported to be more cost and profit efficient than their smaller peers in the intermediation of funds in the Colombian financial system (Sarmiento and Galán, 2017), we expect a positive dependence between financial performance and the probability of being super-spreader, good hub, and good authority. About the concentration of borrowing and lending, we expect an inverse relation between concentration of counterparties and the probability of being a super-spreader; on the other hand, the probability of not being a super-spreader is expected to be high for peripheral financial institutions, which have been documented to concentrate their borrowing relationships (see Afonso et al. (2013) and Cocco et al. (2009), who analyze small financial institutions in the periphery of the U.S. and Portuguese interbank markets, respectively).

Regarding alternative centrality measures, we expect financial institutions' degree ($\mathscr{k}_{it}$), strength ($\mathscr{s}_{it}$), and betweenness ($\mathscr{b}_{ti}$) to coincide with their LSI_{it}. As LSI_{it} is a global measure of centrality that incorporates the number of linked neighbors, the intensity of the linkages at all possible order adjacencies, and the in-between role of vertexes, we expect to observe consistency with degree, strength, and betweenness. The linear dependence (i.e. correlation) between the selected dependent variables supports such expectation (in **Figure 7**).

To select our model we first analyze the *between variation* (across individuals) and *within variation* (for a given individual) of the independent and dependent variables –as suggested by Baltagi (2013). For the dependent variables, we find that within variation is very low: financial institutions with high LSI_{it} are stable over time; that is, super-spreaders tend to be the same throughout the quarters under examination. Using the 99th percentile for the LSI_{it} the share of financial institutions that are super-spreaders along the sample is 70.3%, whereas those who are not super-spreaders account for 97.4%. We also identify that between variation is greater than within variation for the alternative independent variables and for dependent variables. For instance, in the case of $size$, our main variable of interest, the between variation is 1.04 whereas the within variation is only 0.06. Similarly, for leverage the between variation values are 1.04 and 0.28, respectively (see **Table 2.A1**).

The second step was to perform a Hausman Specification Test comparing the estimates from the random effects probit model against a conditional fixed-effects logistic model. The test leads to reject the null hypothesis according to which the logit fixed-effects estimator is efficient, confirming our selection of the probit random effects model.[14].

Table 2.2 shows the results of estimating the probit model in (6). The overall fit of the probit model is adequate for predicting super-spreaders. First, the Wald test is statistically significant for all specifications, thus confirming the overall significance of the proposed model. Second, the ROC statistic (0.966) suggests that the model discriminates between super-spreaders and non-super-spreaders in an accurate manner[15]. That is, the larger the ROC statistic, the most accurate is the model to differentiate super-spreaders. Interestingly, we find that the ROC statistics ranges from 0.812 to 0.932 across the alternative independent variables, indicating that those specifications also have high predicting power.

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[14] This is because of logit fixed-effects estimators rely on within variation rather on between variation (as the random effects probit models does). As a result, the logit fixed-effects model leads to a significant loss of observations due to it drops all observations in which y_{it}=0 for all t or y_{it} is 1 for all t. In our case it drops 80.5% of the observations in order to fit the model. Thus, the logit fixed-effects model leads to substantially higher standard errors (i.e. efficiency loss) because of both the loss of observations and that only within variation of the regressors are used.

[15] ROC statistic tests the predictive accuracy of the fitted probit model by estimating the area under the corresponding receiver operating characteristic (ROC) curves. Thus, the ROC analysis provides a quantitative measure of the accuracy of diagnostic tests to discriminate between two states or conditions (e.g. LSI or non LSI). It has been recently used in the economic literature to test the accuracy of probit and logit models (See, Minoui et al. 2013; Comelli, 2014). Technical details on the implementation of the ROC test can be found in Cleves (2002).

Regarding financial institutions' characteristics, we identify that size is the key significant determinant of the probability of being a super-spreader. This concurs with Craig and von Peter's (2014) findings of large banks that dominate wholesale activity in money markets (i.e. *money center banks*) in the German interbank market. As expected, size is the major determinant of the probability of being a super-spreader, a good hub, and a good authority. Likewise, size is the major determinant of the probability of displaying high degree, strength, and betweenness.

Leverage is the second most relevant factor. There is a positive and significant relation between the likelihood of being a super-spreader and the leverage of financial institutions. This suggests that the more leveraged financial institutions are, the more likely they are central players in the interbank network. As expected, because credit institutions are notably more leveraged than non-credit institutions (i.e. about 2.5 times on average), the significance of leverage as a explanatory variable of the likelihood of being a super-spreader is rather intuitive: not only super-spreaders are large, but they are also more leveraged, consistent with the main features of credit institutions in the Colombian case. Also, this positive relation overlaps with the findings of Martínez and León (2015), who report that there is a significant spatial effect (i.e. a spill-over) caused by leverage on the cost of liquidity in the Colombian money market. As suggested by Martínez and León, this may be related to corporate finance basics: highly leveraged firms have a lower weighted cost of capital, which induces a lower opportunity cost for their liquid funds, and –therefore- they can lend at a lower rate.

Lending concentration has a negative influence on the likelihood to be central in the network. Thus, the more concentrated the lending relationships in the interbank market, the lower the probability to be a super-spreader in the network. That is, as expected, a financial institution should have a diversified lending relationship in order to be a super-spreader; otherwise, its liquidity spreading abilities would be somewhat restricted. Borrowing concentration and financial performance are not significant as determinants of the likelihood of being a super-spreader.

In the case of alternative centrality measures, hub centrality, authority, and betweenness, the probability is also determined by borrowing concentration. Hub centrality and betweenness exhibit a negative sign, which suggests that the less concentrated the borrowing counterparties, the more likely it is to be an important financial institution based on those centrality measures. On the other hand, the sign is positive for authority centrality, which suggests that a financial institution that excels as global borrower (i.e. high authority) concentrates its borrowing; it is safe to say that as the central bank is the dominant source of liquidity lending in the network, those heavily concentrating their borrowing with the central bank should appear as global borrowers. These results and their interpretation are fairly robust to other thresholds for selecting super-spreaders. In **Table 2.A2** we report the results for two different thresholds, namely 95th and 90th percentile super-spreaders. As expected, there is consistency between LSI_i and the alternative dependent variables in these two other specifications.

In this sense, financial institutions do not connect to each other randomly, but they interact based on a size-, leverage-, and diversified lending-related preferential attachment process. The size-related preferential attachment coincides with literature about the role of market power and too-big-to-fail implicit subsidies (e.g. implicit or explicit access to last-resort lending) on the increased likelihood of large financial institutions to appear in both sides (i.e. borrowing and lending) of financial markets, their ability to obtain lower funding rates, and their willingness to engage in riskier activities by means of increasing leverage and risk-taking (Bertay et al. 2013; IMF, 2014). Angelini et at. (2011) find, for instance, that during the global financial crisis of 2008 the cheaper funding cost of larger banks in the U.S. interbank market was associated with the existence of moral hazard risks linked to too-big-to-fail implicit subsidies (see also). Likewise, the size-related preferential attachment process supports evidence of smaller financial institutions relying on stable borrowing and lending relationships with large counterparties (see Cocco et al. 2009; Fecht et al. 2011; Afonso et al. 2013; Braüning and Fecht, 2015).

The leverage-related preferential attachment process may be linked to the fact that credit institutions, which are those that contribute the most to LSI, not only are larger, but are also more leveraged than non-credit institutions. Also, as reported by Martínez and León (2015), the higher leverage of credit institutions may allow them to lend at lower rates because their weighted cost of capital may be relatively lower than that of non-credit institutions, thus enjoying an advantageous position as natural lenders in the interbank funds market. Similarly, the diversified lending-related preferential attachment process may result from credit institutions enjoying the advantages of higher leverage levels, which allow them to serve as natural lenders for other financial institutions.

2.5. Final remarks

In this paper we find that the Colombian interbank funds market displays an inhomogeneous and hierarchical (akin to a core-periphery) connective structure, in which a few financial institutions fulfill the role of super-spreaders of central bank's liquidity within the interbank funds market. Thus, our research work not only contributes to central banks' efforts to analyze the structure and functioning of interbank funds markets, but also contributes to designing liquidity facilities, implementing monetary policy, and identifying those financial institutions with a systemic role in the corresponding market and other related ones (e.g. sovereign securities, foreign exchange, etc.).

Accordingly, four particular contributions of our research work are worth stating. First, we propose a methodological approach that explores the connective structure of the interbank funds network and identifies those financial institutions that may be considered as the most important conduits for monetary policy transmission and for liquidity spreading among participating financial institutions. In this sense, our approach is able to identify interbank funds' systemically important financial institutions, which should be the focus of financial authorities' efforts for preserving financial stability and promoting an efficient monetary policy transmission. Likewise, in the sense of Acharya et al. (2012), the presence of super-spreaders – with market power- could support central bank's virtuous role in the efficiency and stability of the interbank market as credible provider of liquidity to a broad spectrum of financial institutions.

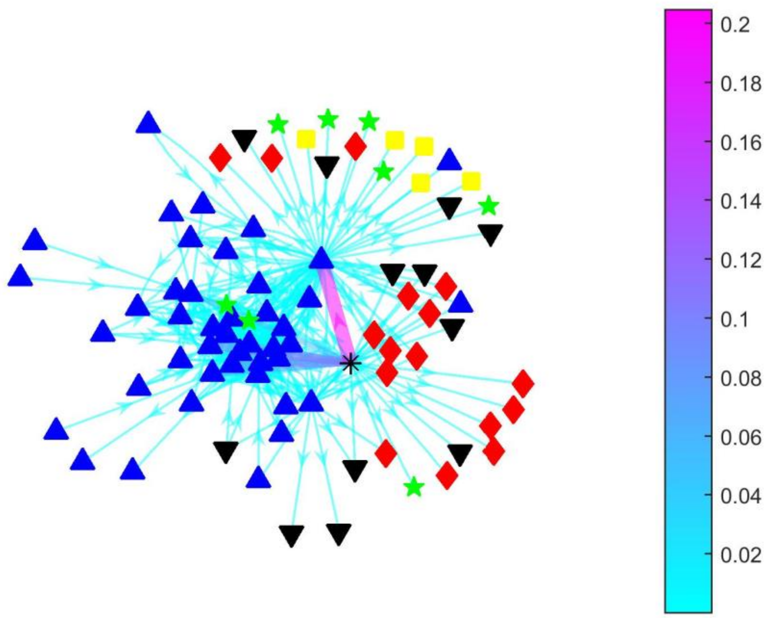
Second, our results support recent findings about the existence of some stylized facts in financial networks, namely an inhomogeneous and hierarchical connective structure that contradicts traditional assumptions in interbank contagion models (i.e. homogeneity, symmetry, linearity, normality, static equilibrium). Confirming the robust-yet-fragile characterization of financial networks by Haldane (2009) entails major challenges for financial authorities contributing to financial stability. For instance, as argued after the crisis (e.g. Kambhu et al. (2007); May et al. (2008); Haldane and May (2011); León and Berndsen (2014)), the most evident challenge comes in the form of focusing financial authorities' preventive actions on super-spreaders, which requires shifting from institution-calibrated to system-calibrated prudential regulation.

Third, as is the case of interbank funds networks in the U.S., Netherlands and Austria, and consistent with the existence of a core-periphery hierarchy, the Colombian interbank funds network is ultra-small, with an average geodesic distance around two. This not only means that the spreading capabilities of interbank funds network are particularly high, either for liquidity or for contagion effects, but it also suggests that the existence of super-spreaders may alleviate the inefficiencies resulting from the under-provision of liquidity cross-insurance in interbank markets documented by Castiglionesi and Wagner (2013).

Fourth, by means of a random effects probit regression model, we confirm that in the Colombian case the probability of being a super-spreader is determined by financial institutions' size, leverage, and lending concentration. These three features characterize credit institutions in the Colombian case. This concurs with evidence from other countries. Accordingly, size may be the main factor behind the interbank funds network's reported scale-free connective structure and its core-periphery hierarchical organization. Nevertheless, as causality may not be inferred from the probit model, it is uncertain whether size is the driving force (i.e. the cause) behind the connective and hierarchical structure of the interbank funds network, or it is the result (i.e. the effect). Moreover, based on complex adaptive systems literature, it may be the case that size is –simultaneously- the driving force and the result of the interbank funds network dynamics by means of feedback effects. Regarding leverage and lending diversification, it is likely that these two features allow credit institutions to enjoy a natural advantage to lend; again, the causality is to be tested.

Further related research work may come in several forms. First, it is imperative to test the robustness of results under stringent financial liquidity conditions, such as a disruption of local or external credit lines, or a contractionary monetary policy; we attempted such test, but available data does not cover periods that could be fair examples of such conditions –for instance, year 2002. Second, the causality in interbank funds networks' dynamics should be explored to understand the role of size and other variables as causes and effects. Third, due to its contribution to money market liquidity, collateralized borrowing should also be considered for identifying central bank's liquidity supers-spreaders.

Figure 2.1. The interbank funds and central bank's repo network



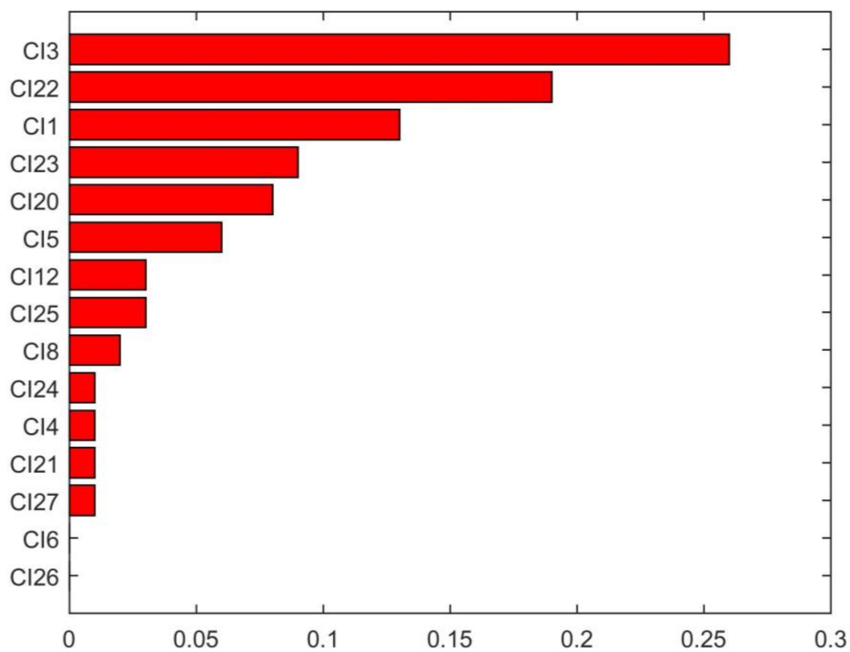
Notes: The direction of the arrow corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. Financial institutions considered are central bank (asterisk), credit institutions (upward-pointing triangles), brokerage firms (diamonds), investment funds (downward-pointing triangles), pension funds (squares), and other financial institution (stars). A force-directed layout (i.e. attraction between adjacent vertexes, repulsion between distant vertexes) is used to distribute vertexes.

Table 2.1. Standard statistics for the interbank funds and central bank's repo network (Averages of 16-quarter sample, 2010Q1-2013Q4)

Statistic	Including the central bank	Excluding the central bank
Participants	74	73
Density	0.09	0.08
Clustering	0.14	0.19
Mean geodesic distance	2.17	2.19
Degree	(In | Out)	(In | Out)
Mean	6.19 | 6.19	5.72 | 5.72
Standard deviation	7.14 | 8.79	6.99 | 7.81
Skewness	1.34 | 1.90	1.31 | 1.63
Kurtosis	3.81 | 7.41	3.77 | 6.49
Power-law exponent	1.91 | 3.13	2.53 | 3.19
Assortativity index	0.55 | 0.18	0.59 | 0.42
Strength	(In | Out)	(In | Out)
Mean	1.35 | 1.35	0.29 | 0.29
Standard deviation	3.83 | 9.14	0.63 | 0.62
Skewness	4.53 | 3.30	8.31 | 2.75
Kurtosis	27.29 | 70.89	17.07 | 11.76
Power-law exponent	1.46 | 1.65	1.45 | 1.55
Assortativity index	0.10 | -0.05	0.23 | 0.20

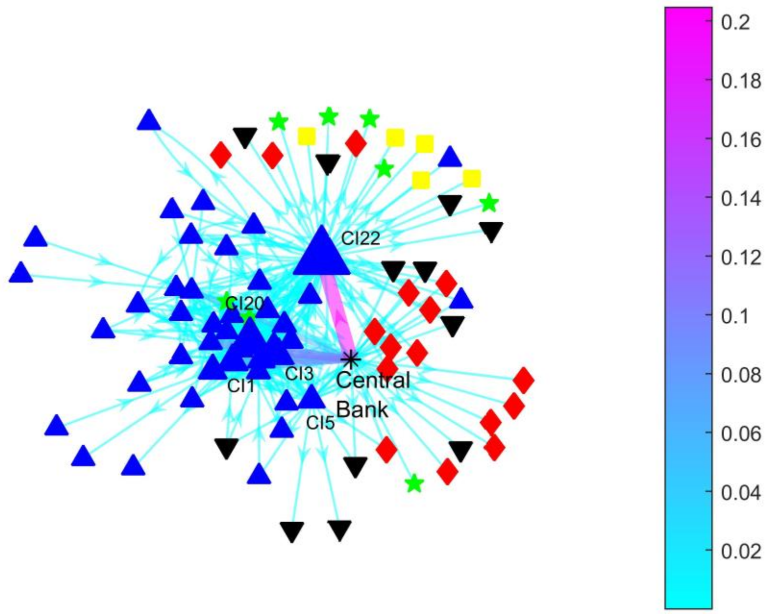
Notes: This table suggests that the interbank funds and central bank's repo network is an approximate scale-free network, akin to other social networks documented in literature, and it resembles a core-periphery structure.

Figure 2.2. Top-15 financial institutions by average LSI_i



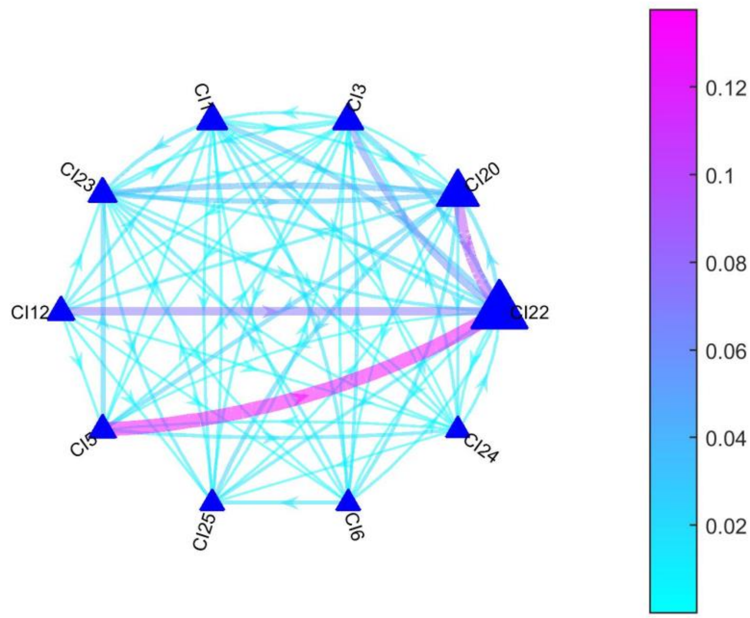
Notes: This figure presents the top-15 financial institutions by average LSI_i estimated on the 16 quarters (2010Q1 to 2013Q4). Credit institutions (CI) dominate the contribution to LSI. Average contributions by other types of institutions are below 0.0%.

Figure 2.3. The interbank funds and central bank's repo network with estimated LSI_i



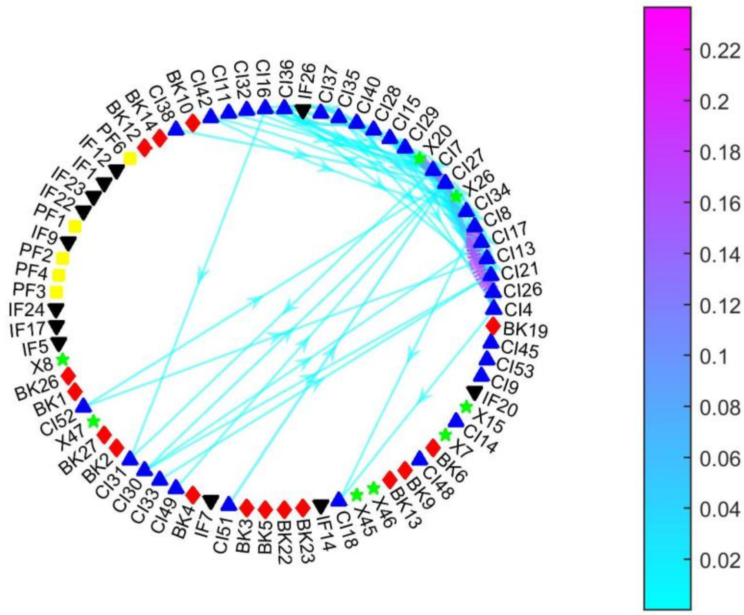
Notes: The size of the vertexes corresponds to the contribution to LSI. The direction of the arrow corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. Financial institutions considered are central bank (asterisk), credit institutions (upward-pointing triangles) brokerage firms (diamonds), investment funds (downward-pointing triangles), pension funds (squares), and other financial institution (stars). A force-directed layout (i.e. attraction between adjacent vertexes, repulsion between distant vertexes) is used to distribute vertexes.

Figure 2.4. The interbank funds core network



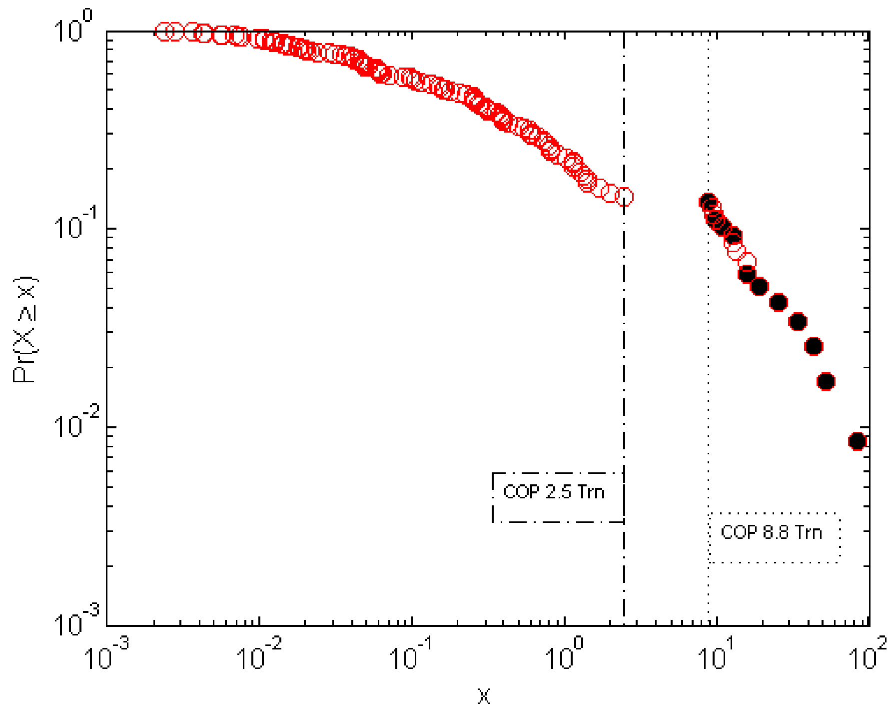
Notes: The size of the vertexes corresponds to the contribution to *LSI*. The direction of the arrow corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. A circle layout is used to distribute vertexes.

Figure 2.5. The interbank funds periphery network



Notes: The size of the vertexes corresponds to the contribution to *LSI*. The direction of the arrow corresponds to the direction of the funds transfer (i.e. towards the borrower), whereas its width and color represents its contribution to the total value of transactions with respect to the color scale on the right. Financial institutions considered are credit institutions (upward-pointing triangles), brokerage firms (diamonds), investment funds (downward-pointing triangles), pension funds (squares), and other financial institution (stars). A circle layout is used to distribute vertexes.

Figure 2.6. Distribution of Colombian financial institutions' size



Notes: There are two different size regimes, in which super-spreaders (filled circles) correspond to large financial institutions. Note that there is a double logarithmic scale. Size corresponds to the 2013 average asset value reported by the Financial Superintendence of Colombia. Based on León (2014).

Figure 2.7. Linear dependence between *LSI* and traditional centrality measures

	LSI	h	a	k	s	b
LSI	1					
h	0.60	1				
a	0.78	0.34	1			
k	0.57	0.67	0.64	1		
s	0.81	0.48	0.98	0.74	1	
b	0.46	0.35	0.55	0.66	0.62	1

Notes: Correlations among variables are computed for all quarters in the sample. The centrality measures are Liquidity Spreading Index (LSI), authority (a), hub centrality (h), degree (k), strength (s), and betweenness (b).

Table 2.2. Likelihood to be a central bank liquidity super-spreader in the interbank market network (Independent variables fitted at the 99th percentile)

Variable [a, b]	LSI_i	h_i	a_i	k_i [h]	s_i	b_i
Size $(size)$ [c]	3.229 (2.82)**	1.637 (2.70)***	4.866 (2.75)***	6.557 (1.96)**	11.335 (3.15)***	1.236 (4.19)***
Leverage (lev) [d]	1.804 (3.30)***	0.189 (0.89)	0.665 (2.10)**	0.541 (2.68)***	0.384 (1.24)	0.804 (3.32)***
Financial performance (roa) [e]	0.136 (0.31)	-0.098 (-0.54)	0.359 (1.67)*	0.154 (1.12)	0.331 (1.55)	0.087 (0.61)
Borrowing concentration $(borr)$ [f]	0.857 (1.69)*	-0.551 (-4.23)***	1.070 (3.50)***	-0.072 (-0.35)	0.046 (0.24)	-0.426 (-3.81)***
Lending concentration $(lend)$ [g]	-2.647 (-4.42)***	-0.185 (-1.08)	-0.011 (-0.08)	-0.501 (-3.17)***	-0.201 (-1.89)*	-0.422 (-3.23)***
Constant	-6.920 (-3.57)***	-1.450 (-4.54)***	-1.951 (-3.09)***	4.404 (3.18)***	-1.720 (-1.66)*	-2.057 (-8.11)***

Observations	1068					
Observations = 1	165	336	318	938	450	237
Wald Chi2 (Prob >chi2)	33.20 (0.000)	76.13 (0.000)	59.61 (0.000)	37.51 (0.000)	49.22 (0.000)	57.57 (0.000)
ROC statistics (Std. err) [h]	0.966 (0.005)	0.9321 (0.008)	0.9042 (0.011)	0.8121 (0.020)	0.8355 (0.013)	0.897 (0.010)

Notes: This table depicts results of a probit model (random effects) run on quarterly data from the period 2010q1 to 2013q4 and estimated by maximum likelihood. [a] Dependent variables correspond to 1 when the financial institution contributes to the 99th percentile of the distribution of the liquidity spreading index (LSI_i) or the alternative network metrics(i.e. h_i, s_i, and b_i), and zero otherwise. All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean). [b] Robust standard errors are clustered at the financial institution level. t-statistics in parenthesis, significant at .10*, .05** and .01***. [c] Assets' value, as reported by the Financial Superintendence of Colombia (SFC). [d] Debt to assets ratio, based on balance sheet data reported by SFC. [e] Return over assets. [f] Herfindahl-Hirschman index on weighted borrowing counterparties. [g] Herfindahl-Hirschman index on weighted lending counterparties. [h] ROC statistics tests the predictive accuracy of the fitted probit model by comparing the areas under the corresponding receiver operating characteristic (ROC) curves.

Appendix

Table 2.A1. Between and within variation of variables used in the probit model

Variable	Between (Std.Dev)	Within (Std.Dev)	Number of observations	Number of individuals
LSI	0.222	0.1032	1068	105
$\mathscr{h}$	0.3006	0.1242	1068	105
$\mathscr{a}$	0.2972	0.1096	1068	105
$\mathscr{k}$	0.4383	0.1533	1068	105
$\mathscr{s}$	0.3441	0.1499	1068	105
$\mathscr{b}$	0.2545	0.1305	1068	105
$size$	0.8187	0.0638	1068	105
lev	1.0452	0.2826	1068	105
roa	1.0278	0.4038	1068	105
$borr$	0.8386	0.3715	1068	105
$lend$	0.9027	0.2612	1068	105

Notes: This table reports between and within variation (standard deviation) of the variables used in the probit model computed during the period 2010Q1 to 2013Q4. T-bar = 10.17 for each variable. Liquidity Spreading Index (LSI), authority ($\mathscr{a}$), hub centrality ($\mathscr{h}$), degree ($\mathscr{k}$), strength ($\mathscr{s}$), and betweenness ($\mathscr{b}$). $Size$ is the asset value in COP million, as reported by the Financial Superintendence of Colombia (SFC); lev is the debt to assets ratio, based on balance sheet data reported by SFC; roa is the return over assets; $borr$ and $lend$ are the Herfindahl-Hirschman indexes on weighted borrowing and lending counterparties, respectively. All statistics are estimated based on original variables (i.e. they are not standardized).

Table 2.A.2. Likelihood to be a central bank liquidity super-spreader in the interbank market network (Independent variables fitted at the 95th percentile)

Variable [a, b]	LSI_i	$\mathscr{h}_i$	a_i	$\mathscr{k}_i$ [h]	$\mathscr{s}_i$	$\mathscr{b}_i$
Size	1.463	1.837	3.716	4.605	6.607	0.933
$(size)$ [c]	(4.14)***	(2.82)**	(4.40)***	(2.46)**	(4.28)***	(4.46)**
Leverage	1.468	0.158	0.480	0.665	0.159	0.923
(lev) [d]	(3.01)***	(0.49)	(0.90)	(3.74)***	(0.61)	(4.31)***
Financial performance	0.310	-0.158	0.356	-0.017	0.219	0.303
(roa) [e]	(0.99)	(-0.59)	(1.36)	(-0.13)	(0.69)	(1.81)*
Borrowing concentration	0.377	-0.238	1.322	-0.743	0.015	-0.374
$(borr)$ [f]	(1.25)	(-1.52)	(4.05)***	(-3.82)***	(0.07)	(-3.39)***
Lending concentration	-0.992	-0.367	-0.195	-0.094	-0.040	-0.364
$(lend)$ [g]	(-2.84)**	(-1.47)	(-0.80)	(-0.82)	(-1.72)*	(-2.08)**
Constant	-4.095	-2.906	-3.572	1.545	-1.177	-2.383
	(-5.50)***	(-6.61)***	(-6.37)***	(2.09)**	(-2.68)***	(-8.24)***
Observations	1068					
Observations = 1	115	218	207	595	262	170
Wald Chi2 (Prob >chi2)	28.81	57.49	61.65	117.07	52.36	44.27
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROC statistics (Std. err) [h]	0.966	0.934	0.956	0.927	0.964	0.896
	(0.006)	(0.011)	(0.007)	(0.008)	(0.007)	(0.011)

Notes: This table depicts results of a probit model (random effects) run on quarterly data from the period 2010Q1 to 2013Q4 and estimated by maximum likelihood. [a] Dependent variables correspond to 1 when the financial institution contributes to the 95th percentile of the distribution of the liquidity spreading index (LSI_i) or the alternative network metrics(i.e. $\mathscr{h}_i$, $\mathscr{s}_i$, and $\mathscr{b}_i$), and zero otherwise. All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean). [b] Robust standard errors are clustered at the financial institution level. t-statistics in parenthesis, significant at .10*, .05** and .01***. [c] Assets' value, as reported by the Financial Superintendence of Colombia (SFC). [d] Debt to assets ratio, based on balance sheet data reported by SFC. [e] Return over assets. [f] Herfindahl-Hirschman index on weighted borrowing counterparties. [g] Herfindahl-Hirschman index on weighted lending counterparties. [h] ROC statistics tests the predictive accuracy of the fitted probit model by comparing the areas under the corresponding receiver operating characteristic (ROC) curves.

Table 2.A.3.Likelihood to be a central bank liquidity super-spreader in the interbank market network (Independent variables fitted at the 90th percentile)

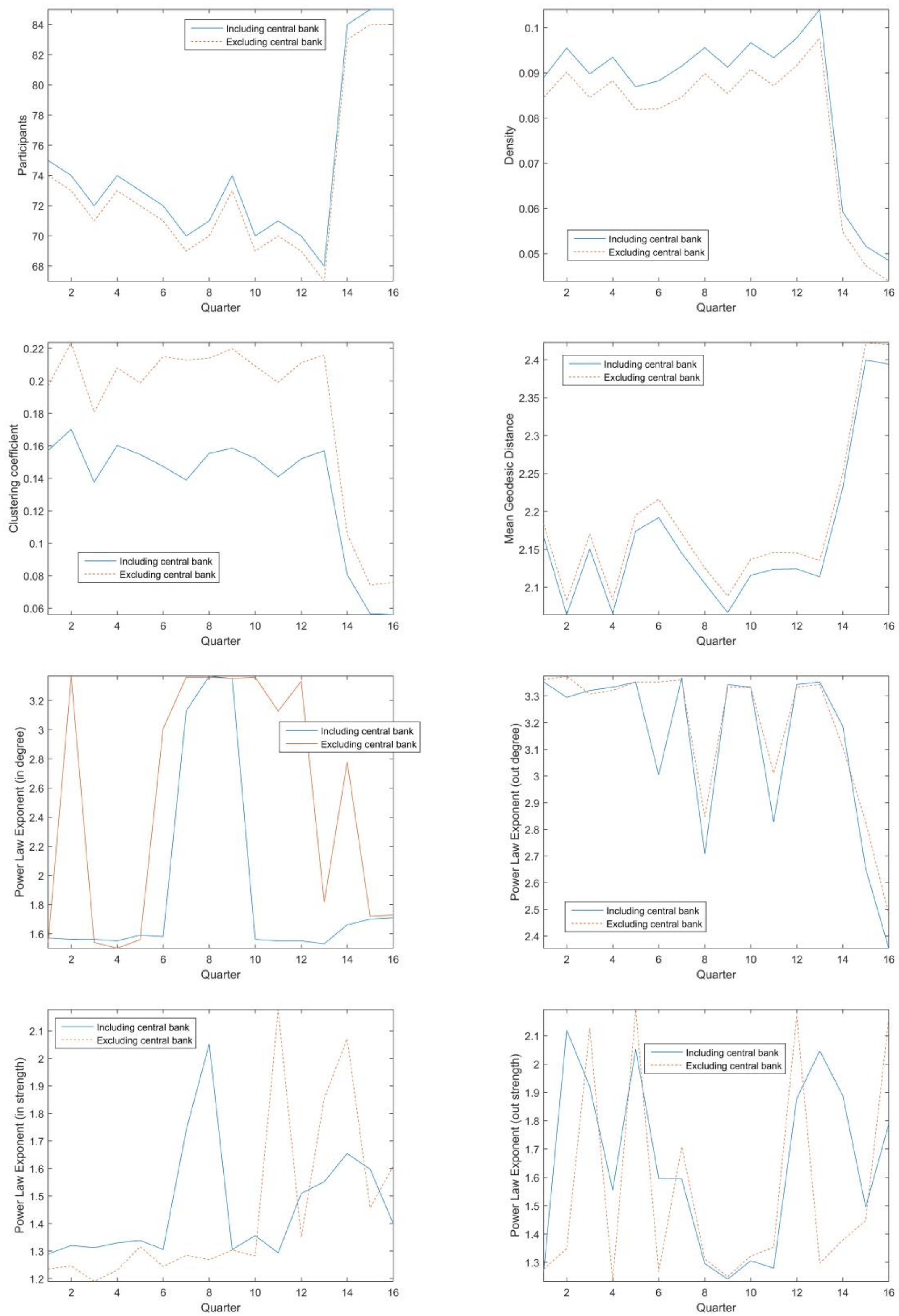
Variable [a, b]	LSI_i	$\hbar_i$	a_i	k_i [h]	s_i	b_i
Size	1.175	1.633	2.031	7.399	4.040	0.939
$(size)$ [c]	(4.31)***	(2.88)***	(4.07)***	(3.93)***	(4.39)***	(4.53)**
Leverage	0.939	0.164	0.739	0.589	0.763	0.712
(lev) [d]	(2.61)***	(0.43)	(1.68)*	(2.31)**	(2.01)**	(3.54)***
Financial performance	0.101	-0.587	0.200	-0.005	0.124	0.300
(roa) [e]	(0.37)	(-2.39)**	(1.01)	(-0.03)	(0.39)	(1.82)*
Borrowing concentration	0.227	-0.711	1.088	-0.549	0.189	-0.341
$(borr)$ [f]	(1.10)	(-3.13)***	(4.04)***	(-4.11)***	(0.72)	(-2.80)**
Lending concentration	-0.701	-0.697	-0.107	-0.467	-0.371	-0.406
$(lend)$ [g]	(-2.58)***	(-1.98)**	(-0.35)	(-3.08)***	(-1.68)*	(-2.27)**
Constant	-2.344	-3.512	-3.119	0.896	-2.723	-2.537
	(-6.75)***	(-6.95)***	(-6.93)***	(1.43)	(-6.04)***	(-8.18)***
Observations	1068					
Observations = 1	88	171	158	455	200	128
Wald Chi2 (Prob >chi2)	103.75	48.93	56.82	86.00	32.77	44.27
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROC statistics (Std. err) [h]	0.969	0.960	0.938	0.929	0.974	0.893
	(0.006)	(0.006)	(0.009)	(0.008)	(0.004)	(0.012)

Notes: This table depicts results of a probit model (random effects) run on quarterly data from the period 2010Q1 to 2013Q4 and estimated by maximum likelihood. [a] Dependent variables correspond to 1 when the financial institution contributes to the 90th percentile of the distribution of the liquidity spreading index (LSI_i) or the alternative network metrics(i.e. $\hbar_i$, s_i, and b_i), and zero otherwise. All independent variables are standard scores of the original variable (i.e. number of standard deviations above the estimated mean). [b] Robust standard errors are clustered at the financial institution level. t-statistics in parenthesis, significant at .10*, .05** and .01***. [c] Assets' value, as reported by the Financial Superintendence of Colombia (SFC). [d] Debt to assets ratio, based on balance sheet data reported by SFC. [e] Return over assets. [f] Herfindahl-Hirschman index on weighted borrowing counterparties. [g] Herfindahl-Hirschman index on weighted lending counterparties. [h] ROC statistics tests the predictive accuracy of the fitted probit model by comparing the areas under the corresponding receiver operating characteristic (ROC) curves.

Table 2.A4. Network metrics

$k_i^{in} = \sum_{j=1}^{n} A_{ji}$ In degree	$k_i^{out} = \sum_{j=1}^{n} A_{ij}$ Out degree
$s_i^{in} = \sum_{j=1}^{n} W_{ji}$ In strength	$s_i^{out} = \sum_{j=1}^{n} W_{ij}$ Out strength
$d = \frac{m}{n(n-1)}$ Density	$\ell_i = \frac{1}{(n-1)} \sum_{j(\neq i)} g_{ij}$ Mean geodesic distance of a vertex
$\ell = \frac{1}{n} \sum_{i} \ell_i$ Mean geodesic distance of a network	$c = \frac{(\text{number of triangles}) \times 3}{\text{number of connected triples}}$ Clustering coefficient
$r_k = \frac{\sum_{ij}(A_{ij} - k_i k_j / 2m) k_i k_j}{\sum_{ij}(k_i \delta_{ij} - k_i k_j / 2m) k_i k_j}$ Where $\delta_{ij} = \begin{cases} 0 \text{ if } i \neq j \\ 1 \text{ if } i = j \end{cases}$ Assortative mixing coefficient (by degree)	$b_i = \sum_{pq} \frac{u_{pq,i}}{v_{pq}}$ Where $u_{pq,i}$ is the number of geodesic paths from p to q that pass through vertex i, and v_{pq} the total number of geodesic paths from p to q Betweenness centrality

Figure 2.A1. Evolution of the interbank and repo network metrics (2010-2013)



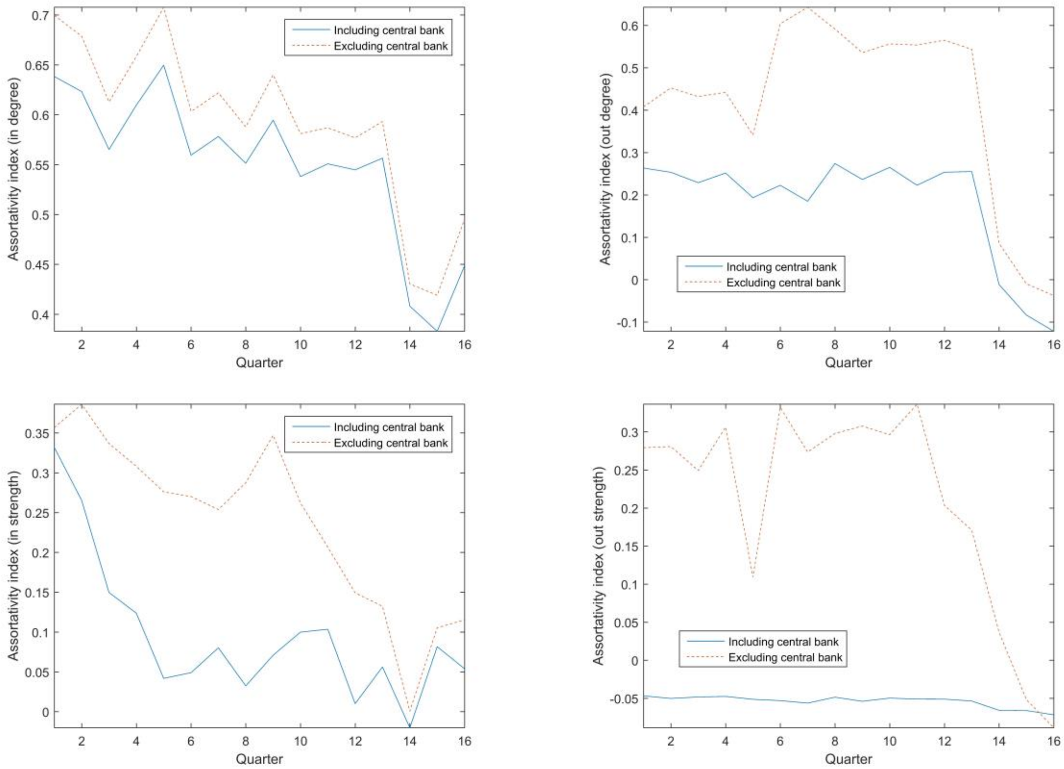
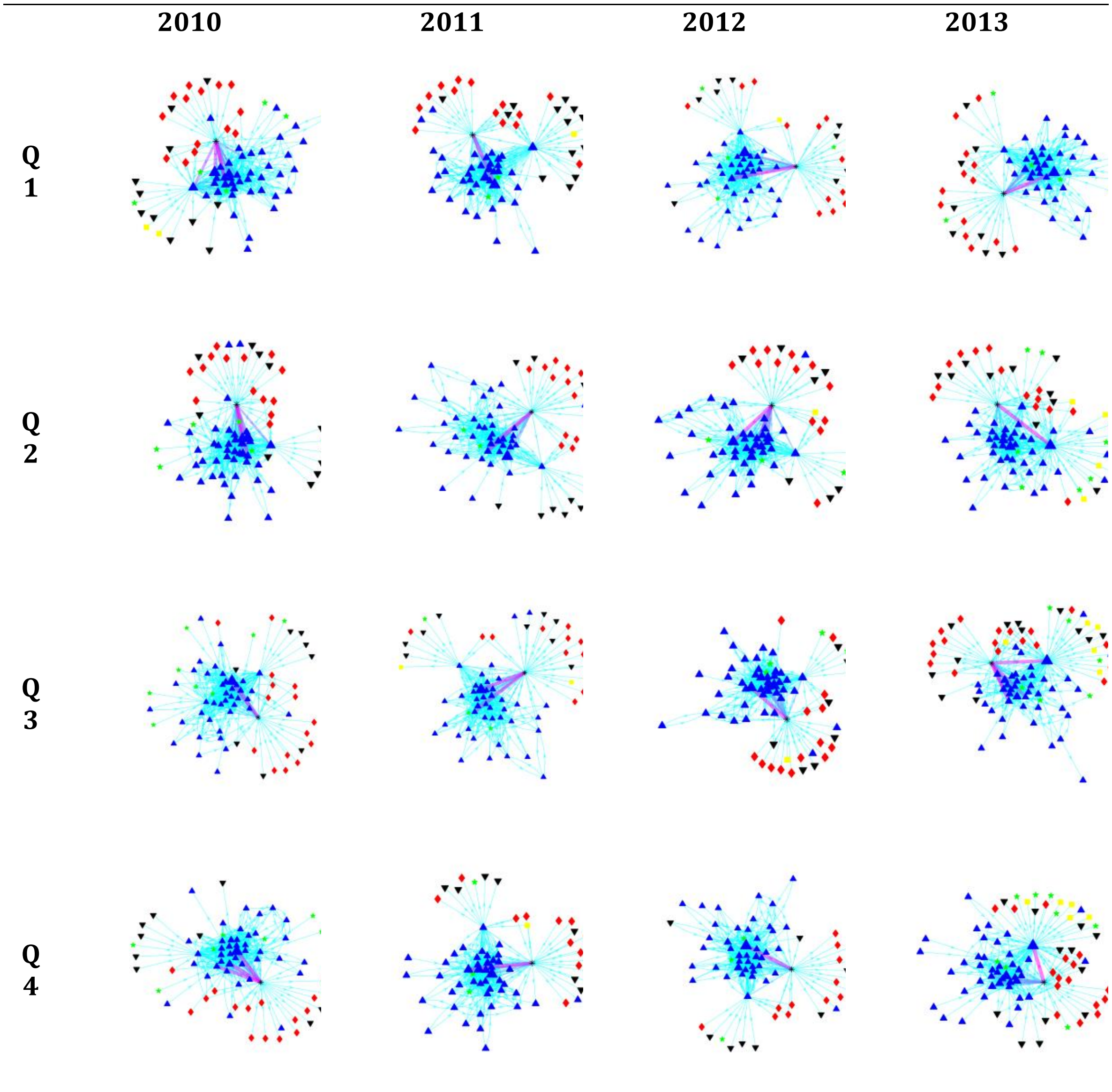

Including central bank
Excluding central bank
Assortativity index (in degree)
Assortativity index (out degree)
Assortativity index (in strength)
Assortativity index (out strength)
Quarter

Figure 2.A.2. Interbank and repo network per quarter



The Influence of Risk-Taking on Bank Efficiency: Evidence from Colombia

3. The Influence of Risk-Taking on Bank Efficiency: Evidence from Colombia

Abstract

This paper shows evidence on the influence of risk-taking on bank efficiency in emerging markets and identifies heterogeneity in the way risk affects banks with different characteristics. We fit a stochastic frontier model with random inefficiency parameters to a sample of Colombian banks. The model provides accurate cost and profit efficiency estimates. The effects of risk-taking on efficiency vary with size and affiliation. Large and foreign banks benefit more from higher exposure to credit and market risk, while domestic and small banks from being more capitalized. We identify some channels explaining these differences and provide insights for prudential regulation.

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3.1. Introduction

During the global financial crisis of 2007-2008, excessive risk-taking was associated with banking runs, fire-sales, reduced lending and financial fragility (Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 2010; Beltratti and Stulz, 2012). In response to this behavior, banking regulators have imposed higher capital and liquidity requirements, leverage ratios, and countercyclical provisions for loan losses, among other regulatory measures (see Basel III standards in BIS, 2010, 2011, 2013). This regulation is intended to discourage risk-taking by imposing higher costs to banks from assuming more risk. Thus, understanding how risk-taking and regulation influences bank performance has become an important concern in the literature (Chortareas et al., 2012; Barth et al., 2013; Berger and Bouwman, 2013).

The aim of this paper is to identify the influence of risk-taking on cost and profit efficiency of banks and to distinguish these effects between banks with different sizes and affiliations. Risk-taking has been identified as a crucial element of the banking production process that should be properly modeled into efficiency measurement (Hughes et al., 2001). Recent evidence shows that failure to account for risk-taking may lead to biased estimations of bank efficiency and misleading estimates of scale economies and cost elasticities (Koetter, 2008; Hughes and Mester, 2013; Malikov et al., 2015).

We contribute to the literature by proposing a stochastic frontier model with random inefficiency coefficients, which allows us to identify the influence of unobserved heterogeneity sources related to risk-taking on bank efficiency. Our approach is close to that in Goddard et al. (2014) and Williams (2012) in which random parameters are used in order to account for unobserved technological and inefficiency heterogeneity. However, we estimate in a single step heterogeneous effects of risk on bank inefficiency, filling this gap in the literature. We account for the influence of credit, liquidity, capital, and market risk exposures and identify differences in the effects that similar levels of risk have on efficiency. The inference of the model is carried out via Bayesian methods (as in Tabak and Tecles, 2010; Hou et al., 2015) that formally incorporate parameter uncertainty and allows deriving bank-specific distributions of efficiency and risk random coefficients.[1]

[1]Our sample is composed by 848 bank-level observations spanned though the period 2002-2012, which then is augmented by using the MCMC algorithm leading to 10,000 iterations that are used for posterior inference (see

The model is estimated for the Colombian banking sector using quarterly bank-level data from 2002 to 2012. We use detailed bank-specific data on liquid assets, securities, credit risk provisions, and core tier capital, provided by the financial regulator and the central bank, used to compute our risk measures. The evaluated period covers several regulatory measures that were implemented to limit bank risk-taking and to promote the foreign entry of banks. In particular, we are interested in to identify the influence of a measure of credit risk based on the borrowers' credit risk ratings on both cost and profit efficiency. This ex-ante measure of credit risk is related to the concept of radical uncertainty of King (2016) in the sense that it tries to incorporate the borrower's behavior as a component of the bank's exposure (i.e. by increasing loan provisions as the borrower becomes riskier).[2] The period considered also allows us to assess the effects of the global financial crisis on the efficiency of Colombian banks.

Our findings remark the importance of accounting for size, affiliation and risk exposure in the estimation of bank efficiency. We find that cost and profit efficiency are over-underestimated when risk measures are not accurately modeled (see Hughes et al., 2001; Koetter, 2008; Radíc et al., 2012, for similar results). Furthermore, we identify that size and foreign ownership are not only important determinants of efficiency but also key characteristics defining the way changes in risk exposures affect cost and profit efficiency. Domestic and small banks benefit more from being highly capitalized, while large and foreign banks benefit from higher exposure to credit and market risk. We find that large banks exhibit higher efficiency than small institutions and that foreign and small banks were more affected by the financial crisis and the regulatory measures introduced after 2008. We explain the main channels supporting these differences in efficiency among banks with different characteristics, which are related to monitoring costs, diversification, information asymmetries, agency costs, and risk-taking incentives. We also identify that the ex-ante credit risk measure captures better risk-taking incentives of banks and hence, it can provide regulators with a more suitable indicator for setting bank provisions for loan losses. Overall, we show that risk-taking plays a crucial role in

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section 4.3. for details). We assess the fit and predictive performance of the alternative models by using DIC and LPS, respectively (Griffin and Steel, 2004). In the robustness section (section 7.3), we present an exercise using an alternative prior distribution for the inefficiency component that confirms our baseline results.

[2] Most of the regulatory measures proposed in Basel II and III are based on traditional assumptions on the distribution of risk (consistent with theories of optimizing behavior), which have been criticized because of their lower efficacy in mitigating large financial shocks (King, 2016).

explaining banking efficiency and the importance of allowing for heterogeneous effects among banks when modeling it.

Our results indicate that large banks face lower costs and present higher incentives to take on more risk in credit and securities markets (compared to small banks). Moreover, we observe that large banks exhibit decreasing returns to scale, suggesting that their cost and profit efficiency gains can obey to external sources such as lower funding costs (i.e. deposits, subordinated debt or interbank loans) as a result of implicit government guarantees (Davies and Tracey, 2014). These findings are consistent with the view that systemic risk tends to increase with bank size (Laeven et al. 2016), which constitutes a signal for regulators to closely monitor the behavior of these banks and their potential accumulation of risk.

The rest of this paper contains seven sections. The second presents related literature. The third describes the Colombian banking sector performance and regulation. The fourth presents the proposed specification, the Bayesian inference, comparison criteria and the empirical models. The fifth describes the data. In the sixth, we present and analyze the main results. The seventh shows robustness exercises. The eighth section concludes, and discusses some regulatory implications from our findings.

3.2. Related Literature

In their pursuit of better performance banks tend to engage on more risk-taking, which depends on competition, regulation and, corporate governance (Boyd and De Nicoló, 2005; Laeven and Levine, 2009; Wagner, 2010; Agoraki et al., 2011; Anginer et al., 2013). However, risk has a cost that is mainly related with banking regulation and market discipline (Hughes and Mester, 2010; Flannery, 2010). Thus, understanding how risk-taking and regulation influences bank performance has become an important concern in the literature.

Our paper is related to studies accounting for the impact of banking regulation on banks' efficiency. This literature has found that stringency of capital regulation is associated with higher bank efficiency, while limiting banking activities discourages efficiency (Chortareas et al., 2012; Barth et al., 2013; Berger and Bouwman, 2013). Other strand of literature has focused on the relationship between credit risk, capitalization and bank efficiency (see the seminal work of Berger and DeYoung, 1997). Most of studies exploring these relationships have found that highly capitalized banks are more cost efficient than banks with low capitalization levels (Kwan and Eisenbeis, 1997; Altunbas et al., 2007; Fiordelisi et al., 2011). Furthermore, banks with low cost efficiency have been found to exhibit higher proportions of bad loans and to be more prone to default (Williams, 2004; Podpiera and Weill, 2008; Tabak et al., 2011).

Studies modeling the effects of risk on efficiency usually incorporate only proxies for credit risk (i.e. ex-post measures such as non- performing loans), and omit other important risks faced by banks such as those related to insolvency, market and liquidity, which may have relevant effects on bank efficiency. One exception in the paper of Radíc et al. (2012) that accounts for several risk measures as inefficiency determinants of investment banks in G-7 countries and find that insolvency and liquidity risk have significant effects on cost and profit efficiency. Evidence on the effects of risk-taking on bank efficiency in emerging economies is more limited.[3].

Our paper also contributes to the literature devoted to understand the effects of bank heterogeneity on banking efficiency. The omission of heterogeneity related to size and type of ownership has been identified as an important source of biases in the estimations of banks inefficiency (Bos et al. 2009; Feng and Zhang, 2012; Goddard et al. 2014). Pessarossi and Weill (2015) find a significant and positive influence of a higher capital ratio on cost efficiency of Chinese banks during 2004-2009, and observe important differences when the effect of capitalization is allowed to vary with the type of ownership. In particular, foreign banks are found to decrease their efficiency when their capital ratio increases. The effects of risk-taking on bank efficiency can be heterogeneous among banks with different types of ownership and sizes. In particular, foreign institutions in emerging countries may present different practices of corporate governance which jointly with specific characteristics of diversification and the expertise of their foreign parents make them to react in a different way than domestic banks to changes in risk exposures (Chen and Liao, 2011; Lensink et al., 2008). Also, small and large

[3] Bitar et al. (2016) find that compliance with the Basel capital requirements enhances bank protection against risk, and improves efficiency and profitability in the Middle East and North African countries. For the same countries, Naceur and Omran (2011) find bank capitalization and credit risk to be positively associated with cost efficiency. Hou et al. (2014) evaluate the efficiency of the Chinese banking system accounting for measures of risk and market structure and find that risk-taking have positive effects on technical efficiency, which in turn has led to an accumulation of risk in the banking sector

banks may present different elasticity of risk exposure given the differences in the incentives they experience when size increases (Bertay et al., 2013; Tabak et al., 2013). Thus, accounting for heterogeneity related to risk exposure is relevant when measuring bank efficiency.

Identifying inefficiency determinants and accounting for heterogeneity is particularly important in the Colombian banking sector given the rapid expansion of the sector in recent years, the important role of foreign institutions and the several mergers and acquisition (M&A) processes that have been carried out. These characteristics have increased the differences in terms of size and capital structure across institutions, which could affect banks' risk-taking behavior and performance. Furthermore, since 2002 several regulatory measures have been implemented by the Colombian regulators in order to enhance loan losses provisions, and to set adequate capital and liquidity requirements able to limit risk-taking. These measures were initially motivated by a profound financial crisis in 1999 that affected several emerging economies (e.g. Russia, South Korea, Thailand and Brazil) and that evidenced the vulnerability of the Colombian banking sector to external shocks. Therefore, we focus on the Colombian banking sector as it allows recognizing differences in the way risk affects different types of banks in order to get more accurate efficiency estimations and a complete understanding of the effects of risk and prudential regulation on bank performance. Previous studies, although failing to control by risk, have found gains in efficiency of Colombian banks in recent years and have identified that large and foreign banks are more efficient than their counterparts (Daude and Pascal, 2015; Galán et al. 2015; Sarmiento et al. 2018). We extend this literature by employing a stochastic frontier model with random inefficiency coefficients, which captures unobserved heterogeneity related to credit, liquidity, capital, and market risk exposures. This is possible because of the use of a detailed bank-specific data on liquid assets, securities, credit risk provisions, and core tier capital, provided by the financial regulator and the central bank, used to compute our risk measures.

3.3. The Colombian banking sector: performance and regulation

During early 1990s the Colombian banking sector was gradually introduced into the global economy by a financial liberalization program following the trend of other Latin American economies (Carvalho et al., 2014). The program eased restrictions for foreign participation in the banking sector, established a kind of universal banking scheme intended to reduce specialization, and implemented financial regulatory measures to promote competition and efficiency in the financial sector.[4] As a result, by 1997 most of state-owned banks were privatized. The share of public banks in the total assets of the financial system dropped from 43% to 13%, the number of financial institutions increased from 91 in 1990 to 155 in 1997 and the ratio of credit to GDP increased from 30% to 44% (Uribe and Vargas, 2002).

The financial liberalization process in Colombia had positive consequences by increasing competition and efficiency, lowering intermediation costs and improving loan quality. Nevertheless, after some years the greater competition with foreign banks resulted in higher risk levels and a subsequent deterioration of loans quality, especially among domestic banks (Barajas et al., 2002). In 1999, the Colombian banking sector was affected by local and external shocks that triggered the financial turmoil and led to a profound financial crisis. The external shock from the Asian financial crisis led to capital outflows and exchange rate deterioration. At local level, the economic downturn and the raise of real interest rates forced to a rapid deterioration of loan quality and eroded the solvency of the financial sector. Previous studies reveal that the financial sector deterioration was related with low loan loss provisions and tiny capitalization levels (Gomez-Gonzalez, 2009). Between 1998 and 2001, several banking institutions failed and other were merged. Banking institutions specialized in mortgage loans were absorbed by large commercial banks. In consequence, the number of banking institutions fell from 100 in 1998 to 57 in 2001 from which only 31 continued as commercial banks. Also, the annual rate of credit growth declined from 30% to -6% during the same period.

Following the domestic financial crisis of 1999, Colombian financial authorities strengthened the regulatory measures intended to enhance adequate provisions for loan losses, and higher capital and liquidity ratios. These regulatory measures were designed under the Basel standards with the aim of accounting for the interaction of credit risk with liquidity and market risk. Since 2002, risky loans (based on internal loans ratings) were designated as the target measure to set banks provisions for loan losses, rather than the traditional NPL. Thus, loan provisions were settled on an ex-ante measure of credit risk instead of being computed using

[4] Colombian banks are not allowed to offer some financial services that are included in the standard universal banking approach such as insurance and trust activities.

an ex-post measure of credit risk (i.e NPL).[5] Market risk was defined as an estimated value by each bank using the Value at Risk (VaR) of its securities portfolio, which was included as an additional component in the capital ratio since 2008 (as proposed in Basel II). Hence, the higher the market exposure the larger the required capital for the solvency ratio.[6] New definitions of equity capital were also implemented to enhance capital quality (Tier 1 and Tier 2). Finally, a short-term liquidity ratio (LR) was required for banks to hedge from liquidity mismatches.[7]

Overall, the above-mentioned regulatory measures have served to influence banks' behavior due to the incorporation of risk-taking. These measures along with other macro-prudential policies implemented in 2007-2008, played an important role in limiting excessive credit growth, currency mismatches and thus to avoid contagion from the global financial crisis.[8] For instance, in May 2007, the central bank established a marginal reserve requirement that attenuates both loan growth and leverage (Gómez et al., 2016). At the same time, the central bank reactivated a reserve requirement for short-term external borrowing and a limit on exchange rate derivatives exposure to prevent potential arbitrages and to limit a potential substitution from local funding to external borrowing. These measures reduced the transmission of the international monetary policy to domestic lending and enhanced the independence of domestic monetary policy (See Dias et al., 2018). Moreover, in July 2007, the regulator implemented a new scheme of loan provisions (based on expected losses) that enhanced the provision requirements on commercial loans, especially for loans granted to small firms and risky borrowers (see, Morais et al, 2018). Nevertheless, as we show further, an important decrease in both cost and profit efficiency was observed during that period, especially for small and foreign banks.

During the period 2002-2012, the Colombian banking sector experienced an expansion that has been accompanied by the arrival of foreign banks. The aggregated value of loans grew 300%

[5] Provisions vary according to borrowers rating, type of credit (i.e. consumer, corporate, mortgage, etc.) and whether the loan has collateral or not.

[6] Capital ratio (CR) should be greater than 9% and is defined as equity capital (CE) over risk-weighted assets (RWA) plus 100/9 of the (VaR). Formally, $CR = CE/[RWA + (100/9)(V aR)]$, where $CR > 9\%$.

[7] LR is the value of liquid assets over short-term liabilities. LR should be positive for maturities of 7 and 30 days, although it can be negative for 14 days maturities in order to account for the reserve requirement that banks have to meet every two weeks. Before LR, regulators used a ratio of liquid assets over volatile liabilities.

[8] However, the decline in cross-border lending from banks in advanced economies to Colombian banks affected domestic lending, and especially trade finance (Ahn and Sarmiento, 2019).

and the investments to assets ratio doubled. Banks increased their competition in the securities market with non-banking institutions (i.e. brokerage firms) and also their participation in the money market for short-term liquidity boosted. Several M&A processes were also carried out, concentrating financial services in a few but large institutions. As a result, increased risk exposure has been observed.[9] This has required the regulator to closely monitor credit and market risk and to face the challenges of dealing with systemic financial institutions (see León et al., 2012; Sarmiento et al., 2017).

Figure 3.1 shows the evolution of ratios related to credit, liquidity, capital and market risk over the period 2002-2012 for 31 commercial banks that operated during this period. The sample is classified between small and large banks and foreign and domestic banks.[10] Overall, Colombian banks exhibit a downward trend in credit and market risk along with stable levels of capitalization and growing liquidity. However, important differences in the level of risk exposure of banks with different characteristics of size and ownership are observed, which coincide with the aforementioned regulatory changes including those adopted in 2007-2008 to meet Basel II standards. We observe that the ratio of risky loans over total loans has declined for all banks although large and domestic banks exhibit higher levels than small and foreign banks. This trend may be related with the introduction of the use of risky loans as an indicator for loan loss provisions in 2002 and the dynamic provision scheme since 2007; even during a period of credit expansion and high economic growth (López et al., 2014; Morais et al, 2018). The ratio of liquid assets over total assets has gradually increased over time, especially for large and foreign banks. Capital ratio seems to be stable for large banks in Colombia while important increases are observed for small and foreign banks from 2008. Likewise, small banks reduced more than large institutions their holdings of securities after the global financial crisis. This may suggest that small banks were more concerned about the effects of exposures in credit and securities markets due to the lower probability of being saved given their size, which made them to highly increase their capital ratios and diminish their market risk exposures (see Berger and Bouwman, 2013, for similar findings in the US banking sector).

[9] In May 2013, Colombian Treasury Bill (TES) prices decreased 20% in two weeks as a result of the uncertainty related to FED's exit strategy (i.e. the US tapering). This led to bank losses of COP 2.32 billion that represented 4.87% of their equity capital. The impact of the US tapering on the funding costs of Colombian banks in the interbank market is evaluated in Sarmiento (2019).

[10] We define small and large banks as those below and above the median of the total assets level, respectively. Foreign banks are those for which more than 51 percent of the bank's equity is foreign owned.

3.3.1. Efficiency of the Colombian banking sector

Early studies of banking efficiency have found evidence of low cost efficiency in the Colombian banking sector during the 90s although some improvements during the first half of 2000s in merged banks (Estrada and Osorio, 2004; Clavijo et al., 2006). Recent studies have provided evidence on improvements in technical efficiency and productivity in the sector but large heterogeneity among banks. Using a non-parametric frontier model, Sarmiento et al. (2018) found that Colombian banks improved in technical efficiency from 2000 until the global financial crisis of 2007-2008 heightened, afterwards efficiency and productivity decreased considerably. They also found M&A to have a significant and positive impact on bank efficiency, and high heterogeneity in efficiency irrespective of banks' size and affiliation.

Galán et al. (2015) estimated input-oriented technical efficiency during the period 2000-2009 using a dynamic Bayesian SFA model. They found out that foreign ownership has positive and persistent effects on efficiency of Colombian banks, while the effects of size are positive but rapidly adjusted. They also identified high inefficiency persistence and important differences between institutions. In particular, merged banks were found to exhibit low costs of adjustment that allowed them to rapidly recover the efficiency losses derived from merging processes.

Moreno and Estrada (2013) studied the role of market power in explaining efficiency gains in Colombian banks during the 2004-2012 period. By using SFA and non-parametric models, they found a positive relationship between market power and efficiency, which is explained by product differentiation that allows banks to gain efficiency while not charging excessive credit prices. Daude and Pascal (2015) documented that in spite of Colombian banks have relatively higher efficiency levels than other Latin American banks, both efficiency and the degree of market contestability are lower compared with banks from other emerging markets. The authors argue that both conditions are associated with the relatively higher intermediation costs of the Colombian banking sector. However, previous applications have not studied the influence of risk-taking on efficiency of Colombian banks, which has a crucial role in explaining bank behavior (Pessarossi and Weill, 2015), and may lead to biased estimations of bank efficiency and misleading estimates of scale economies and cost elasticities (Hughes and Mester, 2013; Koetter, 2008; Malikov et al., 2015).

3.4. Methodology

Frontier efficiency methods have become a very important tool to identify relevant bank inefficiency drivers and to provide useful indicators of performance of the sector and individual institutions. In particular, SFA, firstly introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), presents the advantages of allowing inferences on the parameters, accounting for idiosyncratic errors and modeling firm characteristics that affect directly the inefficiency in a single stage.[11] In this context, bank characteristics related to their risk exposures can be consistently accounted for in cost and profit efficiency estimations.

3.4.1. Heterogeneity and risk in bank efficiency measurement

Distinguishing inefficiency from heterogeneity is an important issue in the efficiency frontier literature. Omitting heterogeneity variables can lead to biased estimations of inefficiency. In the banking literature, Bos et al. (2009) identify these effects on efficiency levels and rankings when observed heterogeneity is omitted. In particular, in the case of risk exposure, Radíc et al. (2012) evaluate a sample of 800 investment banks of G-7 countries during the period 2001-2007 and find that omitting bank risk-taking from efficiency estimations leads to underestimating profit efficiency. The authors also document that risk exposure measures affect directly the inefficiency distribution.

Unobserved heterogeneity has also been found to affect estimations from stochastic frontier models.[12] In applications to the banking sector, Feng and Zhang (2012) find that failure to consider unobserved heterogeneity results in misleading efficiency rankings and mismeasured technical efficiency, productivity growth, and returns to scale. Goddard et al. (2014) compare different fixed effects, random effects and random parameters models in an application to Latin American banks between 1985 and 2010. They find that models with random parameters in the inefficiency distribution perform better in distinguishing heterogeneity from inefficiency as well as important differences on cost efficiency estimations. Williams (2012) applies a model

[11] In contrast, the main nonparametric method of Data Envelopment Analysis is more flexible but provides, in general, deterministic measures for inefficiency and does not allow accounting for inefficiency heterogeneity in a consistent single stage.

[12] Greene (2005) proposes different methods to deal with this kind of heterogeneity both in the frontier and in the inefficiency distribution. In the Bayesian context, Galán et al. (2014) propose the inclusion of a random parameter in the inefficiency component that can be modeled along with other observed covariates and performs well in capturing latent heterogeneity.

with random parameters both in the frontier and in the inefficiency distribution in order to test the quiet life hypothesis in Latin American banks. However, the author follows a two-step procedure where cost efficiency is regressed on a market power index and other bank characteristics, which may lead to biased and inconsistent efficiency estimations (see Wang and Schmidt, 2002).

In this context, our proposal is intended to model unobserved inefficiency heterogeneity sources related to risk exposures and to account for bank characteristics in a single stage. Our approach is close to that in Goddard et al. (2014) and Williams (2012) in the use of random parameters in the inefficiency component. However, we propose to estimate the coefficients associated to the observed covariates in the inefficiency distribution as random. This allows us to obtain in a single stage bank-specific estimates of the effects of risk exposure measures on cost and profit efficiency. This specification is more flexible than imposing interactions of observed covariates with different characteristics of banks.

3.4.2. A stochastic frontier model with random inefficiency coefficients

Since we are interested in identifying unobserved heterogeneity related to the effects of risk on bank inefficiency, we propose a stochastic frontier model where the coefficients of risk exposure measures in the inefficiency distribution are modeled as bank-specific parameters. The proposed specification is the following:

$$
\begin{aligned}
y_{it} &= \mathbf{x}_{it}\boldsymbol{\beta} + v_{it} - u_{it} \qquad (1)\\
v_{it} &\sim N\,(0, \sigma^2_v)\\
u_{it} &\sim \mathrm{Exp}(\lambda_{it})\\
\lambda_{it} &= \exp(\mathbf{z}_{it}\gamma_i),
\end{aligned}
$$

where y_{it} represents the output for firm i at time t, $\mathbf{x}_{it}$ is a row vector that contains the input quantities, β is a vector of parameters, v_{it} is an idiosyncratic error assumed to follow a normal distribution, and u_{it} is the inefficiency component. The inefficiency is assumed to follow an exponential distribution with a firm specific and time-varying parameter λ_{it}, γ_i is a vector of firm-specific parameters intended to capture differences in the effects of covariates across banks on inefficiency, and $\mathbf{z}_{it}$ contains a set of heterogeneity variables with bank-specific effects. In particular, the random coefficients are intended to capture differences in the way similar changes on risk exposures affect efficiency of different types of banks. This specification is also flexible in the sense that some covariates can be modeled with fixed coefficients just by adding constraints of the type $\gamma_i = \gamma$ to the corresponding parameters.

3.4.3. Bayesian inference

The inference of the model is carried out using Bayesian methods. This approach was introduced in stochastic frontier models by van den Broeck et al. (1994) and allows us to formally incorporate parameter uncertainty and derive posterior densities of cost and profit efficiency for every individual bank. We assume proper but relatively dispersed prior distributions throughout. In particular, the distributions assumed for the parameters in the frontier are: $\beta \sim N(0, \Sigma_\beta\, \sigma^2)$ where Σ^{-1} is a precision diagonal matrix with priors set to 0.001 for all coefficients. The variance of the idiosyncratic error term is inverse gamma, which is equivalent to $\sigma_v^{-2} \sim G(a_{\sigma v}^{-2}, b_{\sigma v}^{-2})$ with priors set to 0.001 for the shape and rate parameters, respectively.

Regarding the inefficiency component, its distribution is assumed to be exponential: $u_{it}|\gamma_i,\, z_{it} \sim Exp(\exp(\boldsymbol{z}_{it}\, \gamma_i))$. For the firm-specific inefficiency heterogeneity coefficients, a hierarchical structure is defined, where $\gamma_i \sim N(\gamma, \Sigma_\gamma)$ and $\gamma \sim N(0, \Sigma_\gamma)$ with priors for the diagonal precision matrix Σ^{-1} equal to 0.1 for all the coefficients. In the case we want to restrict the inefficiency covariates to be common to all the observations we define γ as above. Sensitivity analysis is performed to the use of an exponential prior distribution for γ.[13] Results show convergence to roughly the same values after the number of iterations described below. Following Tabak and Tecles (2010) we also explore the sensitivity of the empirical results to the use of a gamma distribution for the inefficiency component, where $u_{it}|\gamma_i, z_{it} \sim Gamma\,(2, \exp(z_{it}\, \gamma_i))$. Results are robust to the use of the alternative inefficiency distribution (see Appendix). Markov Chain Monte Carlo (MCMC) methods and in particular the Gibbs Sampling algorithm with data augmentation, as presented by Koop et al. (1995) for stochastic frontier models, can be used here.[14] The MCMC algorithm involves 50,000 iterations where the first

[13] In this case the inefficiency parameters are chosen to be centered in a given prior mean efficiency value r^* following the procedure in Griffin and Steel (2007), where $\exp(\gamma) \sim \text{Exp}(-\ln r^*)$.

[14] The implementation of our models is carried out using the WinBUGS package (see Griffin and Steel, 2007, for a general procedure).

10,000 are discarded and a thinning equal to 4 is used to remove autocorrelations. Therefore, 10,000 iterations are used for the posterior inference.

We assess the fit and predictive performance of the different models using a version of the Deviance Information Criterion (DIC) called DIC3 and the Log Predictive Score (LPS) (see Griffin and Steel, 2004; Galán et al., 2014, for applications of these criteria to Bayesian SFA models). The former is a stable variant of the within sample measure of fit introduced by Spiegelhalter et al. (2002) commonly used in Bayesian analysis. Defining the deviance of a model with parameters θ as $D(\theta) = -2 \log f(\mathbf{y}|\theta)$, where $\mathbf{y}$ is the data, then $DIC = \overline{2D(\theta)} - D(\overline{\theta})$. However, using an estimator of the density $f(\mathbf{y}|\theta)$ instead of the posterior mean θ is more stable. This alternative specification presented by Celeux et al. (2006) overcomes robustness problems when the original DIC is implemented to random effects and mixture models. The formulation for this criterion is:

$$DIC_3 = -4E_{\theta}[\log \mathrm{f}(\mathbf{y}|\theta)|\mathbf{y}] + 2 \log \hat{f}\ (\mathbf{y}) \tag{2}$$

Regarding LPS, it is a criterion for evaluating the out-of-sample behavior of different models. This criterion was first introduced by Good (1952) and is intended to examine model performance by comparing its predictive distribution with out-of-sample observations. For this purpose, we split the sample into a training and a prediction set. Our prediction set consists of observations corresponding to the last two observed years of every firm in the sample, and the training set contains all the rest. The formula is the following:

$$LPS = -\frac{1}{k}\sum_{i=1}^{k} log f(y_{i,t}|\text{previous data}) \tag{3}$$

where $y_{i,t}$ represents the observations in the predictive set for the *k* firms in the sample and t_i represents the penultimate time point with observed data for firm *i*.

3.4.4. Translog cost and profit models

We use cost and profit functions for the frontier specification in (1), and we represent them with translog multi-product functions. The estimated model is:

$$
\begin{aligned}
Ln\, c_{it} = \; & \beta_0 + \sum_{m=1}^{M} \beta_m lny_{m_{it}} + \sum_{r=1}^{R} \delta_r lnp_{r_{it}} \\
& + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{mn} lny_{m_{it}} lny_{n_{it}} + \frac{1}{2}\sum_{r=1}^{R}\sum_{s=1}^{R} \delta_{rs} lnp_{r_{it}} lnp_{s_{it}} \\
& + \sum_{m=1}^{M}\sum_{r=1}^{R} \eta_{mr} lny_{m_{it}} lnp_{r_{it}} + \kappa_1 t + \frac{1}{2}\kappa_2 t^2 \\
& + \sum_{n=1}^{M} \phi_m t\; lny_{m_{it}} + \sum_{r=1}^{R} \varphi_r t\; lnp_{r_{it}} + v_{it} + u_{it} \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_{it} \sim exp(\lambda_{it}) \\
\lambda_{it} = \; & \exp(\gamma_0 + \textstyle\sum_{h=1}^{H} \gamma_h z_{h_{it}} + \sum_{j=1}^{J} \gamma_{j_i}^* z_{ji_{t-1}}^*)
\end{aligned} \tag{4}
$$

where c represents the total cost, y_m represent the m outputs, p_r are the r input prices, and t is a time trend in order to account for technological change. We also allow accounting for two types of inefficiency covariates affecting cost and profit inefficiency: A group of h bank characteristics modeled in z_h, which are assumed to have common effects on all banks, and a group of j variables in z_j, capturing banks' risk exposure in the previous period and allowed to have specific effects on the inefficiency of each bank. Note that risk covariates are lagged one period to avoid endogenous bank risk taking. In order to overcome the problem of calculations of logarithms of negative profits, we follow the rescaling method (Berger and Mester, 1997) which corrects profit values by a factor equal to the absolute value of the lowest profit plus one. Linear homogeneity of the cost function is achieved by normalizing total costs and input prices by a chosen input price. Symmetry of the cross-effects is accomplished by imposing $\beta_{mn} = \beta_{nm}$, $\delta_{rs} = \delta_{sr}$. In the case of the profit function the dependent variable is the total profit and the sign of the inefficiency component u is reversed.[15]

From (4) cost/profit efficiency of individual banks in each period is computed as:

$$CE_{it} = \exp(-u_{it}). \tag{5}$$

[15] Note that we use the alternative profit function where banks are seen as price-setters in the output market but price-takers in the input market. This allows to account for imperfect com- petition, unmeasured differences in output quality and not completely variable outputs (Berger and Mester, 1997).

Returns to scale (RTS) can be derived from the cost function as the sum of output elasticities as follows:

$$RTS = \left(\sum_{m=1}^{M} \frac{\partial lnC(x, y, t)}{\partial lny_m} \right)^{-1} \tag{6}$$

where a RTS measure less than 1 indicates that the production technology has decreasing returns to scale (DRS). On the other hand, increasing returns to scale (IRS) are observed if the RTS measure is larger than 1, while if it is equal to 1 it indicates constant returns to scale. Finally, technical change (TC) assuming constant returns to scale is given by:

$$TC = \left(\frac{\partial lnC(x, y, t)}{\partial t} \right) \tag{7}$$

where negative values of TC indicate technical regress while positive values would imply technical progress.

3.5. Data

We employ quarterly data from 31 commercial banks operating during the period 2002-2012. This is an unbalanced panel data set composed by 848 bank-level observations provided by the Colombian central bank (Banco de la República) and the FSC. We only include commercial banks in our sample as they employ a relatively similar technology.[16] We follow the financial intermediation approach in which banks employ deposits, labor, and physical capital to produce loans, securities investments, and other financial services.[17] We consider as input prices: the price of deposits (p_1), which is the ratio of interest expenses divided by total deposits; the price of labor (p_2), which is personnel expenses divided by the total number of employees; and the price of physical capital (p_3), calculated as the ratio of operating expenses (i.e. non-interest reduced by personnel) to total fixed assets. As outputs we consider: loans (y_1) including consumer, commercial, mortgage, and microcredit; securities (y_2), which includes public and private bonds holdings, and other securities investments; and off-balance-sheet

[16] We exclude small credit institutions specialized in retail loans and leasing activities, which may operate under a different technology than commercial banks (Hughes et al. 2001). Moreover, those credit institutions only have activity in some markets while commercial banks behave in all credit markets (i.e. mortgage, commercial, consumer, microcredit, as well as in the money and securities markets). Therefore, our analysis focuses only on commercial banks.

[17] Hughes and Mester (1993) show that deposits should be treated as inputs. See, for example, Sealey and Lindley (1977) for a discussion on the intermediation approach.

(OBS) activities (y_3) measured as the ratio of non-interest income over total income. Non-interest income includes securitization, brokerage services, and management of financial assets for clients, which represent an important source of income for banks.[18] Total costs are considered as the sum of interest and non-interest costs and total profit as the earned net profit.

We consider two bank-specific characteristics with common effects on the inefficiency of all banks. Those are, size (z_1), measured as the level of total assets; and foreign ownership (z_2), which is a binary variable taking the value of 1 if more than 50% of bank shares are foreign owned; and 0 otherwise. As aforementioned, these effects have been found to be relevant inefficiency drivers in previous studies. As risk exposure measures, we include measures for credit risk, liquidity, capitalization, and market risk in accordance with the literature and the Colombian financial regulation. Usually, credit risk has been identified as a source of bank inefficiency (Berger and DeYoung, 1997; Williams, 2004).

Our measure of credit risk (z^*) is computed as the ratio of risky loans over total loans.[19] The higher the share of risky loans the higher loan loss provisions required by the regulator. This measure of ex-ante credit risk may avoid biased efficiency estimations that have been identified when using ex-post credit risk measures such as NPL (see Malikov et al., 2015).[20]

Liquidity (z_2^*) is measured as the ratio of liquid assets over total assets, where liquid assets include cash holdings, negotiable and available to sell public and private debt instruments and pledged collateral in repurchase agreement operations. Higher liquid assets prevent banks from maturity mismatches albeit holding those assets can be costless as they have shorter maturities and thus lower returns. Handorf (2014) documents that liquidity has a cost that reduces bank profits via a lower net interest spread.

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[18] Lozano-Vivas and Pasiouras (2014) document the importance of including OBS when measuring cost and profit bank efficiency adjusted by risk. Tabak and Tecles (2010) find that omitting OBS as an output over(under)estimate cost (profit) efficiency results.

[19] Risky loans are based on internal loan ratings performed by banks according to the Colombian regulation. Measures of ex-ante credit risk are more appropriated to identify bank risk- taking in the credit market (see Ioannidou and Penas, 2010).

[20] We perform a robustness check by using NPL as measure of credit risk instead. Results confirm that our ex-ante measure of risky loans captures better the risk-taking incentives of banks (see Section 3.7).

Capitalization (z_3*) is measured as the ratio of capital equity over total assets. Our measure of capitalization is based on two important features. First, Colombian regulation establishes that foreign banks should hold the same minimum capital than local banks in order to operate. This is because foreign banks operate as subsidiaries rather than branches in Colombia, and in turn, they have to hold their own capital. Therefore, our measure of capitalization is comparable across banks with different ownerships. Second, we argue that differences in capitalization levels may signal banks risk appetite and influence their performance (as in Hughes and Mester, 1998; Pessarossi and Weill, 2015).

Market risk exposure (z_4*) is measured as securities investments over total assets. Banks involved in more investment activities may exhibit efficiency gains from diversification (Radíc et al., 2012). Lastly, it is important to remark that all risk variables are included lagged one-period in order to account for inter-temporal effects on inefficiency and avoid reverse causality. **Table 3.1** exhibits the summary statistics of the main variables described above, where all monetary values are expressed in thousands of U.S. dollars at constant prices from the year 2012. Since we are interested in analyzing the differences between small and large banks and foreign and domestic banks, we also present summary statistics disaggregated by these four groups of banks in **Table 3.A1** in the Appendix.[21]

3.6. Results

We estimate three different cost (C1 to C3) and profit (P1 to P3) models from our proposed specification in (4) by including some restrictions on the parameters associated to risk variables and holding size and foreign ownership as covariates in all the models. This is because we are interested in the effects of risk exposure measures as inefficiency determinants. Models C1 and P1 do not include risk exposure variables in the inefficiency, so γ^*_{1i} , γ^*_{2i} ,γ^*_{3i} , γ^*_{4i} = 0. Models C2 and P2 include the risk covariates in the inefficiency but restrict them to have a common effect on the inefficiency for all banks; thus, γ^*_{1i} , γ^*_{2i} ,γ^*_{3i} , γ^*_{4i} = γ^*_1, γ^*_2,γ^*_3, γ^*_4. Models C3 and P3 include the random inefficiency coefficients for the risk exposure variables.[22]

[21] To control for the impact of outliers we drop a total of 6 observations from 2 banks (3 in each case) because of those observations presented extreme values in terms of capital and liquidity ratios. We do not observe an impact from dropping those observations in our results.

[22] We also estimate one additional specification for comparison purposes (models C4 and P4). These models include the risk exposure covariates in the frontier rather than in the inefficiency distribution. Results are shown in the Appendix and exhibit that any of these covariates are relevant when these variables are included in the frontier.

We present the estimation results only for the parameters in the inefficiency distribution, as we are interested in analyzing the effects of size, ownership and risk exposure on efficiency. **Table 3.2** and **Table 3.3** present the posterior mean and probability intervals for the parameters in the cost and profit inefficiency components, respectively. Results for the frontier parameters are presented in the Appendix (**Table 3.7** and **Table 3.8**).[23]

Model comparison indicators lead to similar conclusions in both the cost and profit models.[24] That is, models including measures of risk exposure improve from models omitting these variables (C1 and P1). This suggests that risk-taking is an important determinant of bank efficiency. From the models considering risk exposures, those including random coefficients for the risk covariates in the inefficiency distribution (C3 and P3) exhibit the best fit and predictive performance. These results suggest not only that measures of risk exposure are important efficiency drivers but also that risk has different effects on cost and profit efficiency of banks with different characteristics. This has important implications for efficiency estimations. In **Table 3.2** and **Table 3.3**, we observe that posterior mean cost and profit efficiency are (over)underestimated, respectively, and that their dispersion is lower when risk exposure measures are not modeled as bank-specific in the inefficiency distribution.

We also find differences in the predictive efficiency distributions of cost and profit models (see **Figure 3.A7** in the Appendix). We observe that both location and dispersion of the distributions are affected (see Koetter, 2008, for similar results). In particular, predictive distributions from models including risk in the inefficiency are more symmetric and those derived from models with random coefficients present less dispersion. Overall, these results evidence the importance of accounting for risk-taking and its associated heterogeneity among banks when estimating bank efficiency (see Hughes et al., 2001; Pessarossi and Weill, 2015; Radíc et al. 2012; Malikov et al. 2015, for previous evidence).

This would support the inclusion of these variables as inefficiency drivers. Recently, Radíc et al. (2012) also found evidence to support that risk exposure is more relevant affecting the inefficiency distribution than the frontier.

[23] From the frontier parameter estimates, it is observed that loans, investments, and OBS positively affect cost and input prices in all models. In the case of profits, the relationship is also positive for loans and investments but negative, although not significant, for OBS. This result was also found by Tabak and Tecles (2010) in an application to the Indian banking sector. However, they found loans and investments to be not significant when OBS is included in both cost and profit models.

[24] Lower values for DIC_3 and LPS indicate better fit and predictive performance.

3.6.1. Efficiency determinants

We observe that size and foreign ownership are important efficiency drivers in all the models. Their effects are positive on cost efficiency and negative on profit efficiency. Previous studies have found similar effects. Chen and Liao (2011) document that foreign banks perform better than local banks because they may better deal with risk exposures given cheaper access to funding sources and more diversification. Fries and Taci (2005) find similar results for banks with a majority of foreign ownership in emerging economies. Sturm and Williams (2008) argue that banks from more financially sophisticated nations are more efficient. Curi et al. (2015) document that during the financial crisis subsidiaries perform better than branches. Interestingly, our findings suggest that foreign banks that operate as subsidiaries in Colombia exhibit higher efficiency than local banks.

Regarding size, previous studies have found that large institutions tend to exhibit greater efficiency associated with higher scale economies (Bos and Kool, 2006; Wheelock and Wilson, 2012; Hughes and Mester, 2013). In previous applications to Colombian banks, both foreign and large banks have also been found to be more cost efficient than local and small banks (Moreno and Estrada, 2013; Galán et al., 2015; Sarmiento et al., 2018). This relative advantage of large over small banks has been recently reported as evidence of the too-big-to-fail dilemma where larger banks take advantage of their size to obtain funds at lower cost and to take on more risk (Santos, 2014). There is also evidence suggesting that bank interest costs tend to decline with systemic size (Bertay et al., 2013). Interestingly, we show in the next section that scale economies are not the driving forces of higher efficiency gains from large Colombian banks, which may suggest evidence on too-big-to-fail implicit subsidies.

Size and foreign ownership are also key characteristics determining the way credit and market risk, and liquidity and capitalization levels affect cost and profit efficiency. This is identified through the random coefficient models. We analyze these effects by type of banks (i.e. small vs. large and domestic vs. foreign). On this regard, our approach is close to the one in Pessarossi and Weill (2015), who study the effects of capital on the efficiency of Chinese banks with different sizes and affiliations. However, we include additional measures of risk and perform an analysis a posteriori after allowing for bank-specific coefficients instead of estimating interactions. **Figure 3.2** and **Figure 3.3** present 95% probability intervals of average posterior random coefficients by type of bank in the cost and profit models, respectively.[25] These figures allow us to identify whether the effects of different types of risks on the efficiency of a group of banks are different than those of the respective benchmark group with a probability greater than 95% and, at the same time, if the estimated coefficients for each group are different from 0 with a probability greater than 95%.[26] We observe two main results when bank-specific coefficients are estimated. First, some groups of banks are more affected than others taking the same risk exposures. Second, the effects of risk exposures become relevant as efficiency drivers for some types of banks. We explain in detail these effects in the following subsections by differentiating for type of risk.

3.6.1.1. Credit risk

Credit risk is identified as a key determinant of both cost and profit efficiency though with opposite effects. While credit risk is found to have negative effects on cost efficiency, it affects positively profit efficiency. These results are observed in both the fixed and the random coefficients models and may suggest that assuming higher credit risk exposures implies expending more resources on monitoring and administering problem loans. Berger and DeYoung (1997) also found evidence on this negative effect of problem loans on cost efficiency in U.S. banks and argue that extra costs are represented by additional monitoring, negotiating possible workout arrangements, disposing collateral for possible defaults, defending bank's safety to the market and supervisor, and additional precautions to reserve quality of other loans. In emerging economies, Kirkpatrick et al. (2008) document that bad loans tend to increase bank production costs, reflecting inefficiency in lending. On the other hand, in terms of profit efficiency results indicate that banks may have incentives to engage in higher credit risk given that they earn higher returns from riskier loans (Malikov et al. 2015).

By type of banks, we identify important differences in the way credit risk affect efficiency. Large and domestic banks are found to be less affected in cost efficiency by assuming the same level of credit risk. That is, it is less costly for large and domestic banks to manage problem loans. A possible explanation could be related to the fact that local banks have better information about

[25] These are the average of the values for each bank-specific parameter at every iteration of the MCMC.

[26] The former is true if the 95% probability intervals of the respective benchmark groups do not overlap each other, and the latter is true if the correspondent intervals do not contain the 0.

borrowers, which implies that these banks may incur in lower monitoring costs. As to large banks, they may benefit from scale economies that allow them to incur proportionally in lower costs at the same credit risk levels. Regarding profit efficiency, large and foreign banks benefit more from assuming similar levels of credit risk. These types of banks may take advantage of their recognition in order to charge higher interest rates for loans of similar quality or are exploiting market power benefits (see Boyd and De Nicoló, 2005; Wagner, 2010).

3.6.1.2. Liquidity

Results from our models with fixed and random coefficients suggest that liquidity has relevant effects on the efficiency of Colombian banks. The random coefficients model identifies an important negative effect of liquidity on cost efficiency of domestic and small banks. This suggests that holding the same proportion of liquid assets is more costly for local and small banks compared with foreign and large banks, respectively. This could be explained by the fact that foreign banks may have greater access to interbank markets and to cheaper sources of funding (Chen and Liao, 2011). Similarly, large banks may have higher access to alternative sources of funding. Angelini et al. (2011) and Sarmiento (2019) have found that large banks benefit from lower funding costs in the interbank markets, which may explain the lower impact of holding liquid assets on their cots efficiency. We also find that holding higher liquid assets reduces profit efficiency in both models, possibly due to those assets usually have lower returns. Differences in the way liquidity affects profit efficiency of banks with different characteristics are less relevant. However, the average impact of liquidity on profit efficiency tends to be greater for domestic banks than for foreign banks.

3.6.1.3. Capitalization

We identify that higher capitalization levels lead to higher cost and profit efficiency. Reasons behind these results may be derived from the agency problems between shareholders and managers. Shareholders of highly capitalized banks have more incentives to control better costs and capital allocation than those of thinly capitalized banks. This incentivizes better corporate governance mechanisms that may lead to efficiency improvements. Berger and DeYoung (1997) also suggest an indirect effect through credit risk. That is, highly capitalized banks have less moral hazard incentives to take on higher risk, and therefore they will incur in less costs. Previous studies have found that highly capitalized banks tend to be more efficient than less capitalized banks in developed countries (Kwan and Eisenbeis, 1997; Fiordelisi et al. 2011; Radíc et al. 2012) and emerging economies as well (Naceur and Omran, 2011; De Jonghe et al. 2012; Pessarossi and Weill, 2015).

Results indicate that the effect of capitalization on efficiency differs between banks with different sizes and ownerships. We find that small and domestic banks benefit more from higher capital ratios in both cost and profit efficiency. However, it is worth to notice that the probability that these estimates are lower than those of large and foreign banks is less than 95%. On this regard, Berger and Bouwman (2013) document that small banks benefited more than large banks from increases in capital during the global financial crisis of 2008. Pessarossi and Weill (2015) show that domestic banks in China benefit from having higher capital while the effect for foreign banks is not significant. They argue that Chinese domestic banks have more government guarantees in case of financial distress. This would increase agency costs between shareholders and debt-holders, which would become more important than agency costs between shareholders and managers.

3.6.1.4. Market risk

We find that holding more investments in the bank's portfolio enhances bank efficiency. This result may reflect the benefits from diversification as banks usually invest in private and public bonds to manage liquidity mismatches (Lozano-Vivas and Pasiouras, 2014). Moreover, this result holds when heterogeneous effects are accounted for in the random coefficients models suggesting that market risk is a cost efficiency determinant for any type of bank. Market risk is also found to have positive effects on banks profit efficiency. In this case, the random coefficients model shows strong evidence supporting that these effects are more relevant for large and foreign banks, which would have greater incentives to engage in more market risk. Foreign banks may benefit from their parents expertise on trading securities (Lensink et al. 2008), while large banks may take advantage from being the primary dealers of the Colombian public debt market. The latter condition allows large banks to obtain profits by selling public debt bills to small banks that have to use them as collateral to hedge liquidity either from the central bank or the secured money market (Sarmiento, 2019). Moreover, large and foreign banks may benefit from having more diversified portfolios and access to cheaper funding sources that allow them to get higher returns on their investments (Chen and Liao, 2011).

However, it is important to remark that the fact that large and foreign banks tend to rely more on unstable sources of funding (i.e. money market funding) and to exhibit more market-based-income may lead to financial fragility and to enhance systemic risk (Brunnermeier et al. 2012; Laeven et al. 2016).

3.6.2. Efficiency, technical change and returns to scale

The evolution of cost and profit efficiency over time and by groups of banks is presented in **Figure 3.4**. We observe that large and foreign banks exhibit higher cost efficiency levels than small and local banks. A possible explanation for the differences between banks with different sizes may be related to the fact that large banks might be considered by creditors as too-big-to-fail, which allows them to have access to cheaper funding sources. Small banks have been more volatile in both cost and profit efficiency over time, especially after the global financial crisis, while large banks have been more stable and present higher cost efficiency over the whole period. This may suggest that large banks are less sensitive to environmental conditions, possibly due to more stable funding sources. In the case of small banks, the result might be the opposite because creditors and depositors may ask for higher returns from those banks as a way to exert market discipline (see Wheelock and Wilson, 2012; Bertay et al. 2013; Hughes and Mester, 2013).

Regarding ownership, although foreign banks present higher cost efficiency than local banks, in terms of profit efficiency they exhibit lower scores and much more volatility over the whole period. The highest difference is observed in 2008 coinciding with the global financial crisis. This suggests that foreign institutions were more affected due to their operations and investments in international markets (see Curi et al. 2015). Nevertheless, in the last few years, foreign banks have improved and exhibited an increasing trend in profit efficiency. We compute technical change and returns to scale from Model C3. As we did for the random coefficient parameters, we compute average posterior distributions by groups of banks, which allows us to simultaneously identify through probability intervals whether these groups of banks present technical progress(regress) or scale economies(diseconomies) and whether there are differences between groups of banks with certain probability.[27] **Figure 3.5** shows the 95% probability intervals by groups of banks with similar characteristics of size and ownership. In general, we observe that with a probability higher than 95% all types of banks exhibit technical progress and that it is on average higher for large and domestic institutions, which can be a consequence of the reorganization processes that these institutions carried out during the period including several M&A. Regarding returns to scale, some important differences are found between groups of banks. We observe that while large institutions operate at decreasing returns to scale, small and foreign banks exhibit increasing returns to scale.[28] These results coincide with those reported by Galán et al. (2015), who suggest that M&A processes carried out mainly by domestic and large institutions may lead them to be oversized, while small and foreign banks may still present some potential scale gains. Furthermore, the fact that large banks exhibit decreasing returns to scale may confirm that their efficiency gains obey to external sources such as lower funding costs (i.e. deposits, subordinated debt or interbank loans) as a result of implicit government guarantees. On this regard, Davies and Tracey (2014) evaluated a panel of the largest international commercial banks over the period from 2001 to 2010 and found that large banks benefit from implicit subsidies and that suppressing them makes scale economies disappear. Their results imply that estimated scale economies for large banks are affected by too-big-to-fail considerations. See also Beccalli et al. (2015) for similar results in the European banking system.

3.7. Robustness check

We perform several robustness exercises. First, we split the sample and search for structural changes in the risk-efficiency relationship after 2008. Second, we use an alternative measure of credit risk and check whether using an ex-post measure affects the estimations. Third, we check whether our findings on the relationship between risk and efficiency change when a profitability measure is included as an additional efficiency driver. Finally, as aforementioned we also check robustness of our results to the use of an alternative prior distribution for the inefficiency component.

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[27] We evaluate technical change and returns to scale at every iteration of the MCMC for each bank and then we average the values at each iteration. This procedure is consistent with the way we assess the effect of the risk-taking measures in the inefficiency models.

[28] The probability interval of RTS for domestic banks contains the value of 1, which do not allow us to conclude about decreasing returns to scale for these type of banks with a probability higher than 95%.

3.7.1. Structural changes after 2008

As presented above the evolution of cost and profit efficiency of Colombian banks exhibits changes in magnitude and volatility after 2008. In fact, changes in their credit and market risk exposures, and capital and liquidity ratios were observed. Thus, we check whether the global financial crisis and the regulatory changes adopted after 2008 represented a structural change in the risk-efficiency relationship of Colombian banks. We split the sample and estimate two cost and profit inefficiency random coefficients models: one for the period 2002-2007 (Modesl C5 and P5) and other for the period 2008-2012 (Models C6 and P6). Results of estimations are presented in **Table 3.4**. We observe that, in general, there are no relevant changes in the way credit risk, capital, liquidity, and market risk affects efficiency of Colombian banks.

However, when random coefficients are analyzed by groups of banks, some changes in the effects of capital and credit risk over cost and profit efficiency of small banks are identified. Figure 6 shows the 95% probability intervals of average posterior capital and credit risk coefficients for small and large banks in the four new estimated models. We observe that the negative effect of credit risk on cost and profit efficiency for small banks is significantly greater during 2008-2012 than in the period 2002-2007. Likewise, the positive effect of capital on both types of efficiency is lower after 2008 for small banks. In contrast, the magnitude of these effects on the efficiency of large banks remains unaltered. The fact that only small banks increased their costs associated to similar levels of credit risk and diminished their benefits associated to capitalization after 2008, may suggest that large Colombian banks were either more prepared to operate under a less favorable environment and more strict regulation or that large banks were more confident in receiving public support in case of being needed.

3.7.2. Non-performing loans

In our estimations, we use an ex-ante measure of credit risk based on loan ratings. However, most of studies use NPL as a measure of credit risk. NPL are an ex-post measure of this type of risk since they account for unpaid loans and risk is already materialized. Nevertheless, differences in the way NPL affect efficiency of banks with different characteristics have been found previously. Kwan and Eisenbeis (1997) find negative effects on efficiency of large banks but positive effects for small banks in the US. Thus, we assess the effects on the estimations of using NPL as credit risk measure and whether the ex-ante measure proposed provides additional information and improves estimations. **Table 3.5** presents the posterior estimations for the cost and profit efficiency random coefficients models using NPL. Results suggest that NPL affects negatively cost efficiency, as found when the ex-ante credit risk measure was used. In this case, unpaid loans generate costs derived from negotiating workout arrangements, disposing more collateral for other potential problem loans or defending bank's safety. However, the model using NPL exhibit lower fit and predictive performance, suggesting that the ex-ante variable may provide more reliable estimations. Regarding the profit model, NPL shows no effect on efficiency. This is opposite to the results obtained using the ex-ante measure, which identifies the incentives generated from the risk-return relationship. Hence, fit and predictive performance indicators are poorer when NPL is used and profit efficiency estimations are underestimated (see Malikov et al., 2015, for evidence on biased efficiency estimations when ex-post measures of credit risk are used). From the regulatory perspective, this result is also important given that Colombian banks are required to set their provisions for loan losses according to their risky loans level. As a result, ex-ante credit risk measures may capture better risk-taking incentives of banks and provide regulators with a more suitable indicator for setting bank provisions for loan losses.

3.7.3. Alternative inefficiency distributions and covariates

In the literature previous studies include profitability as an inefficiency driver as well as estimate both gamma and exponential distributions for the inefficiency component (Tabak and Tecles, 2010; Tecles and Tabak, 2010). Accordingly, we include ROA as an explanatory covariate in the inefficiency distribution of both cost and profit models in order to assess whether profitability has an influence along with risk in explaining efficiency. We find that ROA has a statistically significant effect in the cost model (C8), while in the profit model (P8) it has no significant effect. This result indicates, on the one hand, that more profitable banks are more cost efficient, while ROA differences are not relevant as profit efficiency drivers. Interestingly, we find that the impact of ROA in cost efficiency increases the dispersion of efficiency estimates and also mean cost efficiency increases from 0.77 (baseline model) to 0.81 (see **Table 3.5**).

Finally, we estimate all cost and profit models using a gamma distribution instead of an exponential distribution as described in Section 3.3 and following Tabak and Tecles (2010). **Table 3.A9** and **Figure 3.A8** in the Appendix show the posterior estimation for the inefficiency parameters and plot the posterior efficiency distributions, respectively. We find that results of the estimated coefficients re- main regardless of the use of an alternative distribution indicating their robustness. However, we observe that dispersion of efficiency estimates increases with gamma distribution and also we identify lower efficiency levels, especially in the profit models.

3.8. Concluding remarks

Risk-taking is an inherent condition of the banking business. However, traditional studies on bank efficiency have assumed that risk is incorporated into bank output without explicitly modeling its role in explaining efficiency. We present a stochastic frontier model with random inefficiency coefficients, which captures unobserved heterogeneity related to credit, liquidity, capital, and market risk exposures. The model is found to accurately distinguish heterogeneous responses to changes in risk exposures among banks and provides the first empirical evidence on the role of risk-taking in the efficiency of the Colombian banking sector.

Our findings remark the importance of accounting for size, affiliation and risk exposure in the estimation of bank efficiency. Cost and profit efficiency are found to be over-underestimated when risk measures are not properly modeled into the profit and cost functions. We find that size and foreign ownership are not only important determinants of efficiency but also key characteristics determining the way changes in risk exposures affect bank efficiency. The main channels supporting these differences among banks are related to monitoring costs, diversification, information asymmetries, agency costs, and risk-taking incentives.

We identify that an ex-ante measure of credit risk captures better risk-taking incentives of banks than an ex-post measure such as NPL, and may provide regulators with a more suitable indicator for setting bank provisions for loan losses. The decreasing trend on credit risk exposures of Colombian banks, even during a period of large credit expansion and high economic growth, could be related with the use of this measure for regulatory purposes.

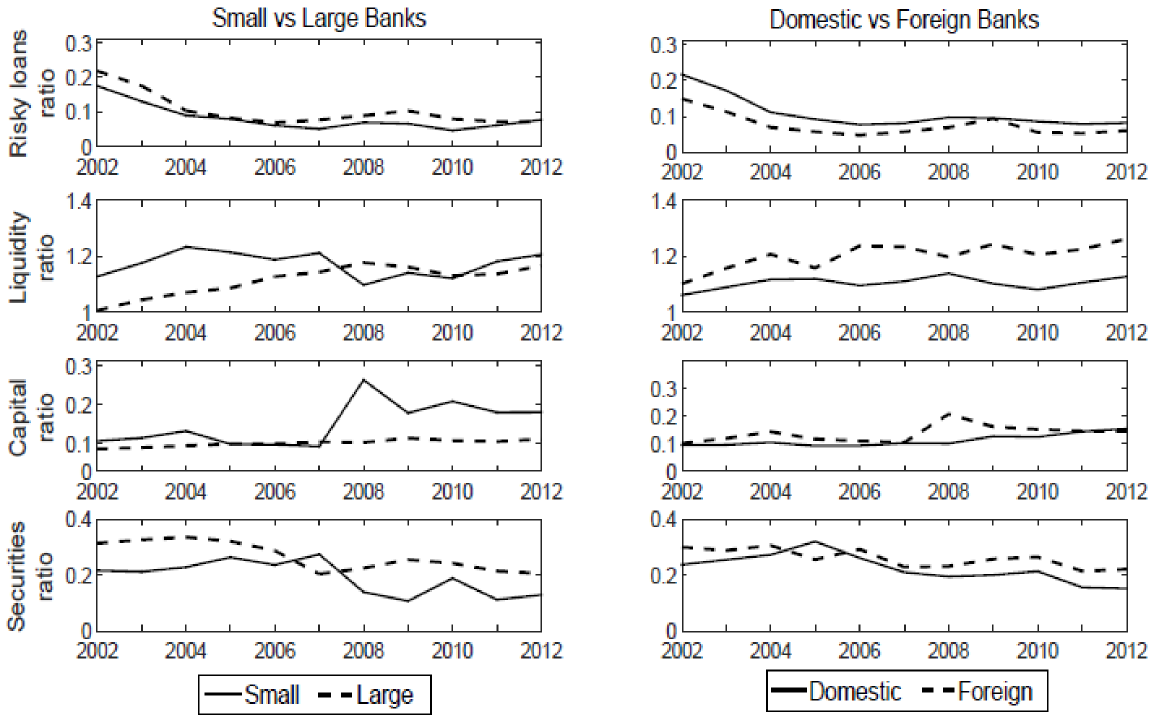
Our results provide evidence to support the hypothesis that capital requirements can contribute to enhance banking efficiency, especially for small and domestic banks, which can be related to agency problems between shareholders and managers. However, we find that the marginal benefits from capitalization are lower for small banks after 2008, coinciding with the global financial crisis and the regulatory changes on capital ratios and credit risk implemented by the Colombian financial regulator, implying that the positive effect of capitalization are limited as the cost of raising capital increases.

Our results also suggest positive effects of market risk on efficiency, especially for large and foreign institutions. These types of banks may benefit from the expertise of their foreign parents, more diversified portfolios and access to cheaper funding sources. Large banks also benefit from being the primary dealers of the Colombian public debt market, which enhances their efficiency gains from the trading activity in this market. However, as large and foreign banks tend to rely more on unstable sources of funding (i.e. money markets) and to exhibit more market-based-income it can leads to financial fragility and enhances systemic risk (Brunnermeier et al., 2012; Laeven et al., 2016).

We observe that large banks exhibited higher efficiency than small institutions and were less affected by the financial crisis (Berger and Bouwman, 2013). This result suggests that large banks were either more prepared to operate under a less favorable environment and more strict regulation or that large bank were more confident in receiving public support in case of being needed. Moreover, the fact that large banks face lower costs and present higher incentives to take on more risk in credit and securities markets constitutes a signal for regulators to closely monitor the behavior of these type of banks and their potential accumulation of risk. Decreasing returns to scale exhibited by large banks may also suggest that their cost and profit efficiency gains obey to external sources such as lower funding costs (i.e. deposits, subordinated debt or interbank loans) as a result of implicit government guarantees (Davies and Tracey, 2014). Thus, regulators should also consider alternative measures to limit risk-taking incentives associated with the fact that large banks may benefit of being considered as too-big-to-fail.

Bank efficiency measures that account for risk-taking constitute a useful indicator for financial stability considerations in emerging markets given that banks with lower efficiency have been found to be more prone to future bank fails and tend to engage on more risk (Tabak et al., 2011). Regulators should be aware not only of the consequences of prudential regulation on bank performance, but also of the different effects that polices intended to discourage risk exposure have on banks with different characteristics related to size and affiliation.

Figure 3.1. Evolution of risk exposure measures by type of bank 2002–2012



Notes: This figure shows the evolution of ratios related to credit, liquidity, capital and market risk over the period 2002-2012 for 31 commercial banks that operated during this period. The sample is classified between small and large banks and foreign and domestic banks. We define small and large banks as those below and above the median of the total assets level, respectively. Foreign banks are those for which more than 51 percent of the bank's equity is foreign owned.

Table 3.1. Summary statistics total sample

Variable	Mean	Median	SD	Min	Max
Total loans	3.207.295	1.988.658	3.911.162	9.383	28.267.020
Securities	1.228.382	838.960	1.255.500	204	6.666.803
OBS	0,0439	0,0345	0,0358	0,0001	0,2650
Price of deposits	0,0066	0,0063	0,0028	0,0004	0,0254
Price of labour	9,0645	7,6186	5,7835	0,0499	66,7323
Price of capital	0,4816	0,2781	0,7507	0,0029	8,8976
Total assets	5.296.408	3.635.674	5.973.928	52.309	41.786.468
Credit risk exposure	0,1110	0,0867	0,0752	0,0037	0,4740
Liquidity ratio	0,2210	0,2060	0,1020	0,0214	0,5800
Capital ratio	0,1160	0,1030	0,0581	0,0448	0,4970
Market risk exposure	0,2400	0,2170	0,1340	0,0005	0,7650
Total cost	295.747	173.610	384.895	5.946	3.546.014
Total profit	20.044	-755	99.533	-261.771	756.685

Notes: This table presents summary statistics of the variables used in the model for the full sample. The variables are computed using quarterly data from 31 commercial banks operating during the period 2002-2012. This is an unbalanced panel data set composed by 848 bank-level observations provided by the Colombian central bank (Banco de la República) and the FSC. All monetary values are in thousands of U.S. dollars at constant prices from 2012.

Table 3.2. Parameters of the inefficiency distribution of cost models

	Model C1		**Model C2**		**Model C3**	
	No risk		*Fixed risk coefficients*		*Random coefficients*	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	1,7158*	[0.9464,2.4853]	0,7982*	[0.2801,1.2322]	0,7586*	[0.2662,1.0968]
γ_1 *size*	-0,3915*	[-0.5443,-0.2386]	-0,3013*	[-0.5546,-0.048]	-0,2871*	[-0.5284,-0.0458]
γ_2 *foreign*	-1,5727*	[-2.5448,-0.6006]	-1,2914*	[-2.0442,-0.5386]	-0,8792*	[-1.3917,-0.3667]
γ_1* *credit*			0,8087*	[0.2632,1.4193]	0,7363*	[0.3783,1.1390]
γ_2* *liquidity*			0,7494*	[0.2891,1.2097]	0,8243*	[0.1009,1.3935]
γ_3* *capital*			-1,2505*	[-1.9249,-0.576]	-2,1452*	[-2.9732,-0.9802]
γ_4* *market*			-0,2269*	[-0.3838,-0.07]	-0,27224*	[-0.5605,-0.084]
Mean efficiency	0,9087		0,9031		0,7710	
s.d. efficiency	0,0982		0,1109		0,1477	
DIC$_3$	2237,07		1812,33		1359,87	
LPS	-12,03		-76,96		-114,74	

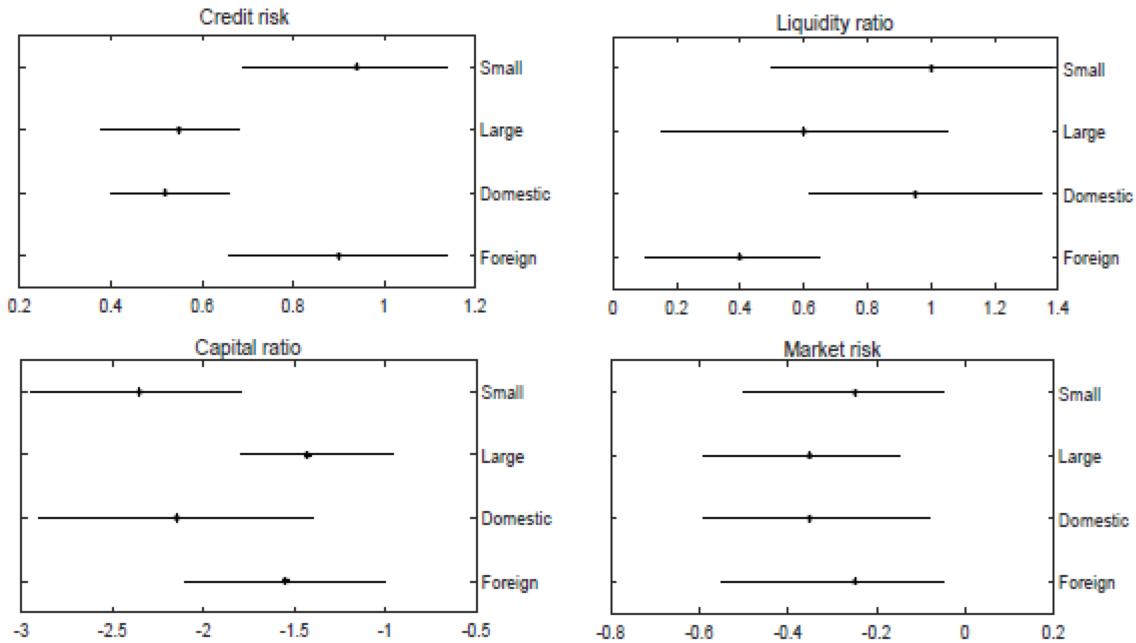
Notes: This table presents posterior mean and 95% probability intervals of parameters in the inefficiency distribution of cost models. Values for $\gamma*_1$ to $\gamma*_4$ in Model C3 correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. Negative coefficients imply positive effects on cost efficiency and the opposite is true for positive coefficients.

Table 3.3. Parameters of the inefficiency distribution of profit models

	Model P1		**Model P2**		**Model P3**	
	No risk		*Fixed risk coefficients*		*Random coefficients*	
	Mean	95\% PI	Mean	95\% PI	Mean	95\% PI
γ_0	-0,9282*	[-1.0649,-0.7916]	-1,1810*	[-1.3774,-0.9847]	-1,2622*	[-1.472,-1.0523]
γ_1 *size*	0,5633*	[0.4765,0.6501]	0,6635*	[0.5619,0.7651]	0,6385*	[0.5407,0.7363]
γ_2 *foreign*	0,4563*	[0.6873,1.3594]	0,4456*	[0.1848,0.7064]	0,5100*	[0.2115,0.8085]
γ_1* *credit*			-1,7314*	[-3.1426,-0.3201]	-1,42308*	[-2.583,-0.2631]
γ_2* *liquidity*			0,4893*	[0.0599,0.9187]	0,8930*	[0.1093,1.6766]
γ_3* *capital*			-1,7583*	[-2.3555,-1.1611]	-1,7240*	[-2.3096,-1.1385]
γ_4* *market*			-0,8969*	[-1.6564,-0.1373]	-1,0484*	[-1.8384,-0.4484]
Mean efficiency	0,5643		0,5787		0,6883	
s.d. efficiency	0,1448		0,1758		0,2068	
DIC$_3$	2534,41		1843,58		1763,09	
LPS	-198,01		-362,90		-424,47	

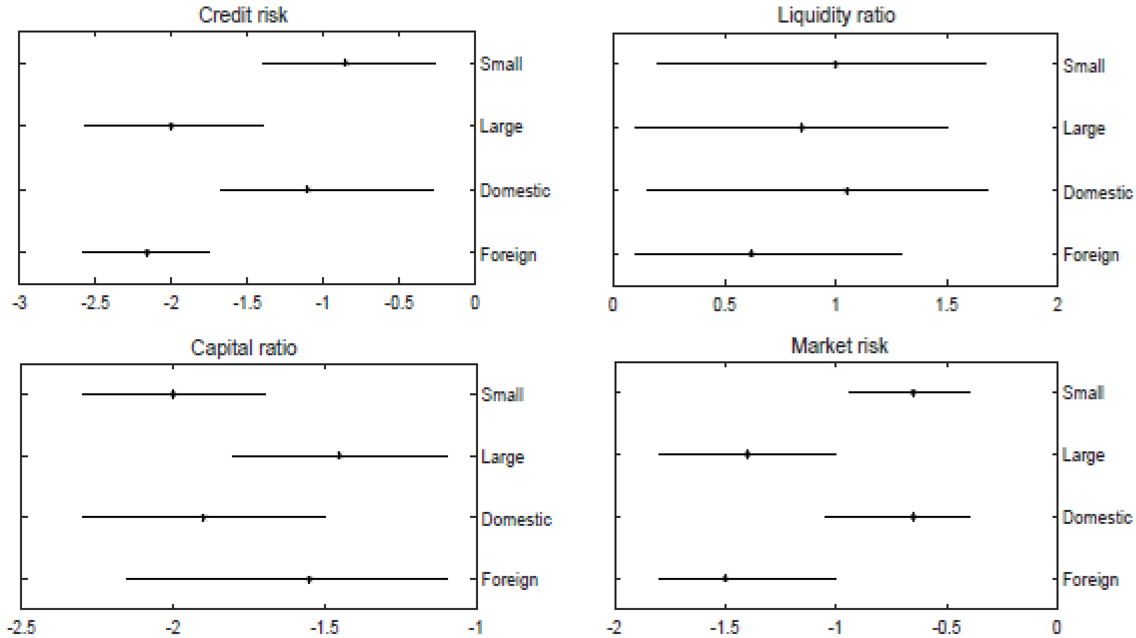
Notes: This table presents posterior mean and 95% probability intervals of parameters in the inefficiency distribution of profit models. Values for γ_{*1} to γ_{*4} in Model P3 correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. Negative coefficients imply positive effects on profit efficiency and the opposite is true for positive coefficients.

Figure 3.2. Probability intervals of risk exposure coefficients by type of bank in cost efficiency (model C3)



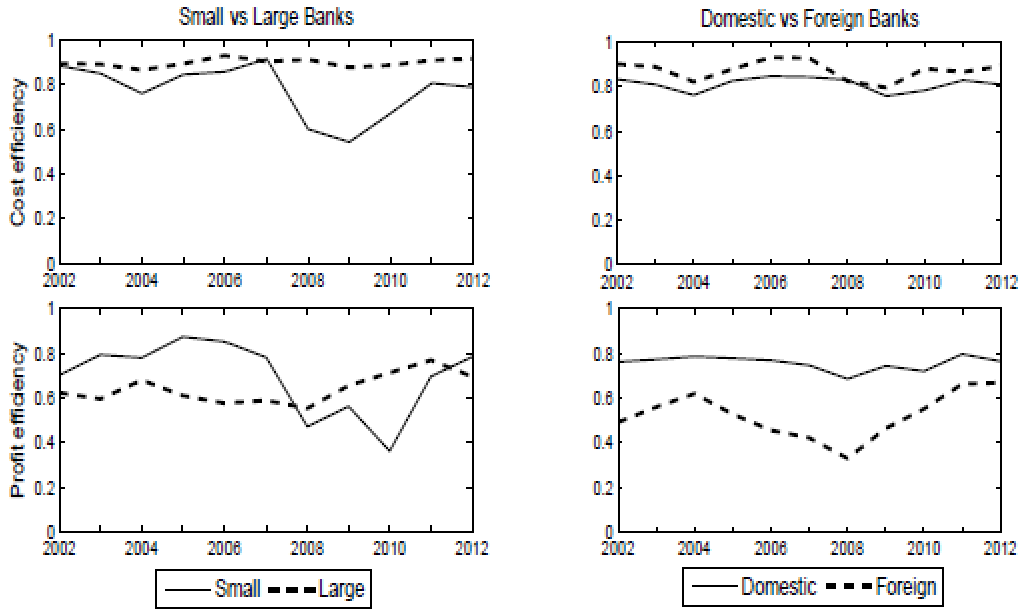
Notes: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the intervals do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply a positive effect of risk on efficiency and positive values imply a negative effect of risk on efficiency.

Figure 3.3. Probability intervals of risk exposure coefficients by type of bank in profit efficiency (model P3)



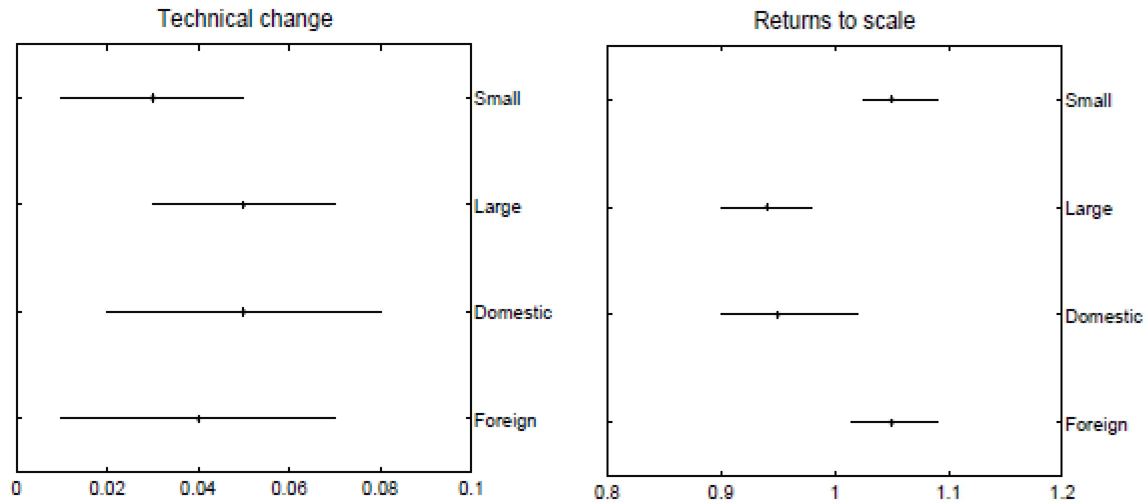
Notes: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the intervals do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply a positive effect of risk on efficiency and positive values imply a negative effect of risk on efficiency.

Figure 3.4. Evolution of mean posterior cost and profit efficiency by groups of banks in random coefficient models



Notes: Figures plot the mean of the average posterior cost and profit efficiency distribution for each group of banks and period. These are the average of the posterior efficiency values for each bank at every iteration of the MCMC.

Figure 3.5. Probability intervals of technical change and returns to scale by groups of banks



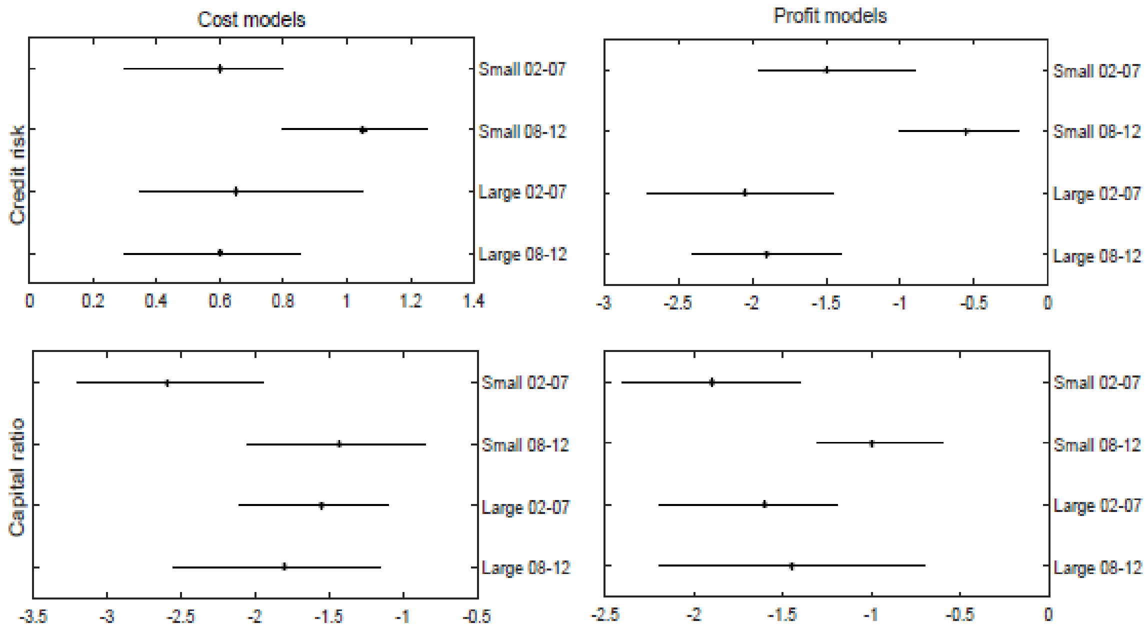
Notes: Figures show the 95% probability density intervals of average posterior distributions of TC and RTS for each group of banks. These are the average of the values for each bank evaluated at every iteration of the MCMC. If the intervals do not overlap each other, the estimates of technical change and RTS for one group are different from the other with probability greater than 95%. In the case of TC, if the intervals do not contain 0, then we can conclude in favor of technical change with a probability greater than 95%. In particular, from (7), TC > 0 imply technical progress and TC < 0 imply technical regress. In the case of RTS, if the intervals do not contain 1, we can conclude following (6) in favor of DRS (RTS < 1) or IRS (RTS > 1) with a probability greater than 95%.

Table 3.4. Parameters of the inefficiency distribution in random coefficients models (sub-sample periods 2002-2007 and 2008-2012)

	Model C3a (2002 – 2007)		Model C3b (2008 – 2012)		Model P3a (2002 – 2007)		Model P3b (2008 – 2012)	
	Mean	95\% PI	Mean	95\% PI	Mean	95\% PI	Mean	95\% PI
γ_0	0,7256*	[0.2546,1.0491]	0,7949*	[0.2789,1.1493]	-1,2215*	[-1.4246,-1.0184]	-1,2535*	[-1.4619,-1.0451]
γ_1 size	-0,2720*	[-0.5006,-0.0434]	-0,3208*	[-0.5904,-0.0512]	0,4840*	[0.4099,0.5581]	0,6825*	[0.578,0.787]
γ_2 foreign	-0,8260*	[-1.3075,-0.3445]	-0,9844*	[-1.5582,-0.4106]	0,4569*	[0.1895,0.7242]	0,5213*	[0.2162,0.8264]
γ_1* credit	0,6833*	[0.2583,1.1072]	0,7895*	[0.2984,1.2793]	-1,5721*	[-2.6535,-0.7907]	-1,3438*	[-2.4391,-0.2484]
γ_2* liquidity	0,7196*	[0.0095,1.4085]	0,8358*	[0.0111,1.636]	0,9409*	[0.1152,1.7666]	0,7374*	[0.0903,1.3846]
γ_3* capital	-2,3460*	[-3.2514,-1.0719]	-1,8924*	[-2.6229,-0.8647]	-1,8190*	[-2.4368,-1.2012]	-1,4641*	[-2.2614,-0.6669]
γ_4* market	-0,2167*	[-0.3666,-0.0669]	-0,1160*	[-0.1962,-0.0358]	-1,1003*	[-1.9294,-0.4706]	-1,0036*	[-1.7599,-0.4293]
Mean efficiency	0,8453		0,7627		0,6518		0,7106	
s.d. efficiency	0,1215		0,1547		0,1804		0,2246	
DIC₃	1362,23		1361,40		1766,36		1765,45	
LPS	-112,04		-112,69		-417,97		-421,90	

Notes: This table presents posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models for the sub-sample periods 2002-2007 and 2008-2012. Values for γ_{1*} to γ_{2*} correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. Negative coefficients imply positive effects on efficiency and the opposite is true for positive coefficients.

Figure 3.6. Probability intervals of credit risk and capital: small vs large banks, 2002-2007 and 2008-2012



Notes: Figures depicts the 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the intervals do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply positive effects of risk on efficiency and positive values imply a negative effect of risk on efficiency.

Table 3.5. Inefficiency parameter distributions in random coefficients models using NPL as an alternative measure of credit risk

	Model C7		Model P7		Model C8		Model P8	
	NPL		*NPL*		*ROA*		*ROA*	
	Mean	95\% PI	Mean	95\% PI	Mean	95\% PI	Mean	95\% PI
γ_0	0,9867	[0.3712,1.5425]	-1,4975	[-1.9154,-1.0127]	0,4552	[0.1597,0.6581]	-1,1359	[-1.3248,-0.9471]
γ_1 *size*	-0,3120	[-0.5028,-0.1071]	0,6019	[0.4276,0.7951]	-0,1915	[-0.3655,-0.0175]	0,5747	[0.4866,0.6627]
γ_2 *foreign*	-1,0026	[-1.3549,-0.6484]	0,6147	[0.2918,0.9580]	-1,0045	[-1.6154,-0.5936]	0,4590	[0.1904,0.7277]
γ_1* *credit*					0,6427	[0.0871,1.1643]	-1,2808	[-2.3247,-0.2368]
γ_2* *liquidity*	0,7617	[0.0538,1.4630]	0,8006	[0.0542,1.5929]	0,7419	[0.0098,1.4522]	0,8037	[0.0984,1.5089]
γ_3* *capital*	-1,9483	[-2.7376,-0.9708]	-1,6938	[-2.2651,-1.1855]	-1,9307	[-2.6759,-0.8822]	-1,5516	[-2.0786,-1.0247]
γ_4* *market*	-0,1950	[-0.3685,-0.0264]	-1,0136	[-1.6913,-0.2328]	-0,2450	[-0.4145,-0.0756]	-0,9436	[-1.6546,-0.4036]
γ_5* *NPL*	0,6569	[0.1907,0.9973]	-0,1235	[-0.4107,0.2314]				
γ_6* *ROA*					-1,3878	[-2.5052,-0.2704]	0,0417	[-0.6652,0.7486]
Mean efficiency	0,7836		0,6708		0,8123		0,7045	
s.d. efficiency	0,1437		0,1951		0,1815		0,2011	
DIC₃	1419,51		1811,90		1353,83		1876,19	
LPS	-105,46		-331,85		-116,04		-351,62	

Notes: This table presents posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models using NPL. NPL are included as the ratio of non-performing to total loans in the previous period. Values for γ_{1*} to γ_{4*} correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. Negative coefficients imply positive effects on efficiency and the opposite is true for positive coefficients.

Appendix

Table 3.A6. Summary statistics by groups of banks

	Small Banks (n=416)					Large Banks (n=432)				
Variable	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Total loans	985.515	826.879	667.003	9.383	2.696.732	5.346.787	3.451.866	4.503.450	758.826	28.267.020
Securities	379.716	256.449	344.862	204	1.393.741	2.045.615	1.775.987	1.272.240	334.376	6.666.803
OBS	0,0471	0,0374	0,0397	0,0001	0,2650	0,0408	0,0325	0,0313	0,0001	0,2150
Price of deposits	0,0079	0,0075	0,0028	0,0004	0,0254	0,0053	0,0052	0,0021	0,0009	0,0118
Price of labour	10,5659	8,4528	7,3962	1,3291	66,7323	7,6186	7,2293	2,8862	0,0499	18,2958
Price of capital	0,5895	0,2764	1,0177	0,0029	8,8976	0,3754	0,2797	0,2997	0,0058	2,8417
Total assets	1.619.551	1.235.202	1.115.449	52.309	3.545.718	8.837.084	6.195.099	6.581.894	3.547.137	41.786.468
Credit risk exposure	0,1170	0,0882	0,0882	0,0037	0,4740	0,1040	0,0861	0,0596	0,0342	0,3670
Liquidity ratio	0,2090	0,1860	0,1180	0,0214	0,5800	0,2310	0,2190	0,0819	0,0328	0,4900
Capital ratio	0,1320	0,1080	0,0747	0,0623	0,4970	0,1010	0,0981	0,0280	0,0448	0,1780
Market risk exposure	0,2190	0,1990	0,1470	0,0005	0,7650	0,2600	0,2340	0,1160	0,0725	0,5580
Total cost	105.691	85.114	76.139	5.946	491.070	478.765	292.534	465.953	50.346	3.546.014
Total profit	1.002	-1.920	22.485	-108.206	77.188	38.381	5.984	135.260	-261.771	756.685

	Domestic Banks (n=547)					Foreign Banks (n=301)				
Variable	Mean	Median	SD	Min	Max	Mean	Median	SD	Min	Max
Total loans	3.983.266	2.399.882	4.399.050	11.552	28.267.020	1.797.142	1.038.357	2.208.175	9.383	11.322.972
Securities	1.519.082	1.059.576	1.387.424	204	6.666.803	700.101	464.628	716.145	795	2.776.628
OBS	0,0451	0,0357	0,0353	0,0001	0,2650	0,0418	0,0318	0,0367	0,0001	0,2150
Price of deposits	0,0060	0,0060	0,0025	0,0004	0,0186	0,0076	0,0073	0,0030	0,0021	0,0254
Price of labour	6,8401	6,5064	2,4024	0,0499	17,6841	13,1796	11,3445	7,5630	1,3291	66,7323
Price of capital	0,3693	0,2525	0,5344	0,0058	8,8976	0,6840	0,4032	1,0065	0,0029	7,5630
Total assets	6.560.745	4.256.538	6.675.098	116.867	41.786.468	2.998.759	2.101.320	3.384.305	52.309	16.983.860
Credit risk exposure	0,1220	0,0944	0,0799	0,0072	0,4740	0,0895	0,0767	0,0606	0,0037	0,3210
Liquidity ratio	0,2120	0,2000	0,0901	0,0214	0,5800	0,2360	0,2130	0,1190	0,0328	0,5770
Capital ratio	0,1100	0,0994	0,0545	0,0448	0,4750	0,1290	0,1120	0,0624	0,0553	0,4970
Market risk exposure	0,2320	0,2120	0,1190	0,0005	0,5580	0,2530	0,2290	0,1570	0,0068	0,7650
Total cost	348.859	198.416	440.633	15.837	3.546.014	199.230	119.698	224.506	5.946	1.533.103
Total profit	33.628	1.687	120.780	-261.771	756.685	-4.642	-1.940	21.740	-96.572	55.599

Notes: This table presents summary statistics of the variables used in the model for the full sample. The variables are computed using quarterly data from 31 commercial banks operating during the period 2002-2012. This is an unbalanced panel data set composed by 848 bank-level observations provided by the Colombian central bank (Banco de la República) and the FSC. All monetary values are in thousands of U.S. dollars at constant prices from 2012. We define small and large banks as those below and above the median of the total assets level, respectively. Foreign banks are those for which more than 51 percent of the bank's equity is foreign owned.

Table 3.A7. Frontier parameter distributions in cost models

	Model C1 *No risk*		Model C2 *Fixed risk coefficients*		Model C3 *Random risk coefficients*		Model C4 *Risk in frontier*	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	5.0904*	[4.011,6.296]	5.2911*	[4.426,6.188]	4.8096*	[3.691,6.065]	5.5647*	[4.498,6.603]
β_1	0.0373*	[0.002,0.097]	0.0207*	[0.003,0.043]	0.0611*	[0.003,0.123]	0.0922*	[0.039,0.132]
β_2	0.0649*	[0.001,0.152]	0.0554*	[0.005,0.152]	0.0281*	[0.001,0.076]	0.0697*	[0.006,0.175]
β_3	0.0333*	[0.001,0.083]	0.0361*	[0.003,0.077]	0.0400*	[0.002,0.127]	0.0221*	[0.001,0.052]
β_{11}	0.0427*	[0.012,0.077]	0.0468*	[0.018,0.077]	0.0524	[-0.002,0.096]	0.0743*	[0.044,0.104]
β_{12}	0.0149	[-0.03,0.055]	0.0095	[-0.031,0.048]	0.0017	[-0.056,0.067]	-0.0602*	[-0.106,-0.014]
β_{13}	-0.0039	[-0.009,0.000]	-0.0035	[-0.008,0.001]	-0.0023	[-0.008,0.003]	-0.0011	[-0.005,0.003]
β_{22}	0.0093	[-0.028,0.047]	0.0126	[-0.021,0.046]	0.0026	[-0.060,0.056]	0.0974*	[0.046,0,147]
β_{23}	0.0014	[-0.002,0.004]	0.0012	[-0.001,0.004]	0.0010	[-0.002,0.004]	-0.0011	[-0.004,0.002]
β_{33}	0.0009*	[0.000,002]	0.0008	[-0.001,0,002]	0.0011	[-0,000,0,003]	0.0004	[-0,001,0,002]
δ_1	0.0618*	[0,002,0.174]	0.0594*	[0,004,0.143]	0.0384*	[0.001,0.114]	0.0976*	[0.002,0.206]
δ_2	0.0721*	[0.003,0.247]	0.0690*	[0.005,0.164]	0.0606 *	[0.002,0.189]	0.0450*	[0.002,0.099]
δ_{11}	0.0878*	[0.034,0.129]	0.0746*	[0.023,0.115]	0.0159	[-0.063,0.087]	0.0542	[-0.006,0.102]
δ_{12}	-0.0885*	[-0.12,-0.052]	-0.0825*	[-0.111,-0.052]	-0.0587*	[-0.102,-0.014]	-0.0660*	[-0.099,-0.031]
δ_{22}	0.0804*	[0.039,0.120]	0.0743*	[0.039,0.109]	0.0732 *	[0.030,0.113]	0.0482*	[0.007,0.089]
η_{11}	0.0829*	[0.055,0.11]	0.0821*	[0.057,0.106]	0.0893*	[0.048,0.128]	0.0771*	[0.049,0.104]
η_{12}	-0.0164	[-0.042,0.008]	-0.0159	[-0.037,0.006]	-0.0195	[-0.051,0.015]	-0.0119	[-0.034,0.010]
η_{21}	-0.0096	[-0.041,0.014]	-0.0156	[-0.047,0.009]	-0.0539*	[-0.094,-0.013]	-0.0260	[-0.053,0.000]
η_{22}	-0.0460*	[-0.070,-0.017]	-0.0414*	[-0.064,-0.018]	-0.0241	[-0.055,0.007]	-0.0286*	[-0.052,-0.005]
η_{31}	0.0007	[-0.003,0.005]	0.0009	[-0.002,0.004]	0.0018	[-0.002,0.006]	0.0004	[-0.003,0.004]
η_{32}	0.0019	[-0.002,0.006]	0.0012	[-0.002,0.005]	-0.0009	[-0.006,0.003]	0.0026	[-0.001,0.006]
κ_1	-0.1037*	[-0.178,-0.027]	-0.1077*	[-0.170,-0.045]	-0.0928*	[-0.158,-0.03]	-0.1086*	[-0.172,-0.045]
κ_2	0.0007	[-0.002,0.003]	0.0007	[-0.002,0.003]	0.0015	[-0.001,0.004]	-0.0002	[-0.003,0.002]
φ_1	0.0109*	[0.004,0.018]	0.0112*	[0.006,0.017]	0.0109*	[0.006,0.017]	0.0107*	[0.005,0.017]
φ_2	-0.0103*	[-0.015,-0.003]	-0.0105*	[-0.015,-0.006]	-0.0108*	[-0.015,-0.006]	-0.0090*	[-0.014,-0.005]
φ_3	0.0001	[-0.000,0.000]	0.0000	[-0.000,0.000]	-0.0002	[-0.000,0.000]	0.0000	[-0.000,0.000]
ϕ_1	-0.0120*	[-0.02,-0.003]	-0.0125*	[-0.020,-0.006]	-0.0116*	[-0.02,-0.004]	-0.0127*	[-0.021,-0.005]
ϕ_2	0.0050	[-0.002,0.012]	0.0050	[-0.001,0.011]	0.0030	[-0.003,0.009]	0.0032	[-0.003,0.01]
ω_1							0.0538	[-0.221,0.334]
ω_2							-0.0755	[-0.236,0.086]
ω_3							0.2936	[-0.043,0.614]
ω_4							-0.4360	[-0.848,0.000]
DIC_3	2237.07		1812.33		1359.87		2119.65	
LPS	-12.03		-76.96		-114.74		-20.10	

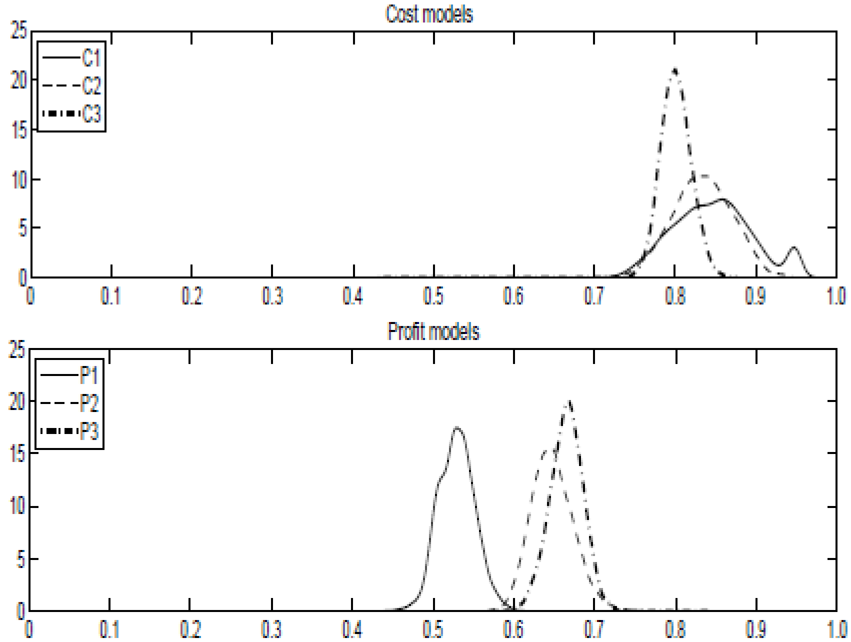
Notes: This table presents posterior mean and 95% probability intervals of the parameter distributions in cost models. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. In Model C4 risk covariates are included in the frontier.

Table 3.A8. Frontier parameter distributions in profit models

	Model P1		Model P2		Model P3		Model P4	
	No risk covariates		*Fixed risk coefficients*		*Random risk coefficients*		*Risk in frontier*	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	8.8101	[-1.462,16.767]	3.3282	[-4.316,13.527]	6.4845*	[1.579,12.170]	8.8857	[-2.738,15.876]
β_1	2.1175*	[0.456,3.637]	2.8217*	[1.147,4.327]	2.0398*	[0.869,2.997]	2.4465*	[0.884,3.889]
β_2	2.3737*	[1.126,3.735]	3.2102*	[1.989,4.350]	2.4766*	[1.705,3.224]	2.8854*	[1.617,4.030]
β_3	-0.1391	[-0.274,0.009]	-0.1828	[-0.305,0.045]	-0.1485	[-0.237,0.054]	-0.1523	[-0.293,0.021]
β_{11}	-0.2742*	[-0.428,-0.121]	-0.3065*	[-0.465,-0.151]	-0.2395*	[-0.350,-0.103]	-0.3395*	[-0.464,-0.181]
β_{12}	0.2138*	[0.058,0.367]	0.2456*	[0.074,0.412]	0.1850*	[0.042,0.310]	0.3075*	[0.151,0.446]
β_{13}	0.0139*	[0.002,0.026]	0.0122*	[0.003,0.022]	0.0102*	[0.002,0.018]	0.0141*	[0.001,0.026]
β_{22}	0.0083	[-0.086,0.117]	0.0231	[-0.086,0.146]	0.0381	[-0.057,0.156]	-0.0622	[-0.158,0.065]
β_{23}	-0.0027	[-0.015,0.010]	-0.0009	[-0.010,0.008]	0.0009	[-0.004,0.006]	-0.0040	[-0.012,0.003]
β_{33}	0.0005	[-0.002,0.003]	0.0008	[-0.002,0.003]	-0.0011	[-0.003,0.000]	0.0013	[-0.002,0.005]
δ_1	-0.6712	[-1.923,0.939]	-1.7524*	[-2.989,-0.338]	-1.3228*	[-2.137,-0.449]	-1.1864	[-2.644,0.022]
δ_2	0.3282	[-0.692,1.218]	0.9088	[-0.098,1.680]	0.6580	[-0.156,1.159]	0.6532	[-0.246,1.611]
δ_{11}	0.0716	[-0.056,0.228]	-0.0117	[-0.120,0.106]	-0.0174	[-0.101,0.068]	0.0410	[-0.060,0.169]
δ_{12}	-0.0003	[-0.149,0.127]	0.0380	[-0.073,0.132]	0.0332	[-0.030,0.094]	0.0176	[-0.103,0.112]
δ_{22}	-0.0307	[-0.177,0.137]	-0.0600	[-0.168,0.071]	-0.0817*	[-0.152,-0.012]	-0.0696	[-0.195,0.089]
η_{11}	0.0937	[-0.061,0.229]	0.1752*	[0.008,0.301]	0.1294*	[0.040,0.217]	0.1346*	[0.007,0.273]
η_{12}	0.0676	[-0.039,0.175]	0.0200	[-0.079,0.123]	0.0610	[-0.005,0.124]	0.0349	[-0.075,0.130]
η_{21}	0.0028	[-0.063,0.077]	-0.0243	[-0.085,0.041]	-0.0164	[-0.059,0.024]	-0.0023	[-0.063,0.053]
η_{22}	-0.0680	[-0.150,0.004]	-0.0498	[-0.114,0.015]	-0.0625*	[-0.103,-0.019]	-0.0520	[-0.123,0.016]
η_{31}	-0.0048	[-0.016,0.009]	-0.0086	[-0.018,0.003]	-0.0050	[-0.011,0.002]	-0.0065	[-0.020,0.005]
η_{32}	-0.0030	[-0.013,0.007]	0.0022	[-0.008,0.011]	-0.0018	[-0.008,0.004]	0.0003	[-0.009,0.013]
κ_1	-0.1007	[-0.305,0.123]	-0.1629	[-0.329,0.005]	-0.1532*	[-0.255,-0.051]	-0.1089	[-0.282,0.065]
κ_2	0.0020	[-0.004,0.008]	-0.0016	[-0.006,0.003]	-0.0003	[-0.003,0.003]	0.0009	[-0.004,0.007]
φ_1	0.0197*	[0.003,0.036]	0.0248*	[0.010,0.038]	0.0233*	[0.013,0.033]	0.0176*	[0.001,0.033]
φ_2	-0.0068	[-0.017,0.004]	-0.0067	[-0.015,0.003]	-0.0091*	[-0.015,-0.003]	-0.0049	[-0.014,0.006]
φ_3	-0.0009	[-0.002,0.000]	-0.0007	[-0.002,0.000]	-0.0005	[-0.001,0.000]	-0.0008	[-0.002,0.000]
ϕ_1	0.0146	[-0.006,0.038]	0.0131	[-0.003,0.030]	0.0072	[-0.002,0.017]	0.0101	[-0.007,0.031]
ϕ_2	-0.0162	[-0.041,0.009]	-0.0157	[-0.032,0.002]	-0.0131*	[-0.022,-0.004]	-0.0140	[-0.034,0.003]
ω_1							-0.3028	[-0.802,0.209]
ω_2							-0.4596	[-0.777,0.128]
ω_3							-0.1873	[-0.764,0.454]
ω_4							0.0495	[-0.666,0.755]
DIC_3	2534.41		1843.58		1763.09		2329.63	
LPS	-198.01		-362.90		-424.47		-254.82	

Notes: This table presents posterior mean and 95% probability intervals of the parameter distributions in profit models. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. In Model P4 risk covariates are included in the frontier.

Figure 3.A7. Predictive distributions of efficiency for cost and profit models



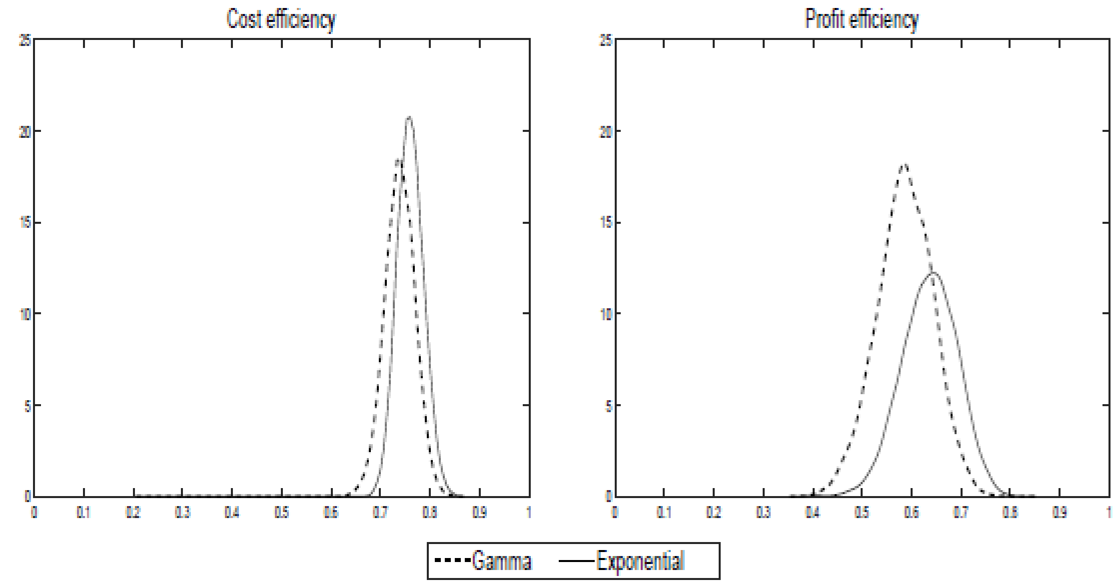
Notes. These figures depicts predictive efficiency distributions of cost and profit models. Models with no risk-taking covariates (C1 and P1), models with common risk coefficients (C2 and P2), and models with random risk coefficients (C3 and P3).

Table 3.A9. Inefficiency parameter distributions in random coefficients models using a gamma distribution

	Model C9		Model P9	
	Mean	95\% PI	Mean	95\% PI
γ_0	0,8134	[0.2987,1.1363]	-1,1934	[-1.3516,-1.0540]
γ_1 *size*	-0,2435	[-0.4523,-0.0908]	0,5279	[0.4115,0.6473]
γ_2 *foreign*	-1,2539	[-1.7284,-0.7192]	0,6326	[0.3510,0.8854]
γ_1* *credit*	0,6952	[0.3090,0.9516]	-1,3147	[-2.0682,-0.6348]
γ_2* *liquidity*	0,8351	[0.0192,1.4572]	0,8135	[0.1693,1.4256]
γ_3* *capital*	-1,9360	[-2.6157,-1.3745]	-1,6518	[-2.0719,-1.1425]
γ_4* *market*	-0,2075	[-0.4136,-0.0351]	-0,9872	[-1.7015,-0.5160]
Mean efficiency	0,7244		0,6376	
s.d. efficiency	0,1625		0,2331	
DIC$_3$	1350,24		1791,37	
LPS	-116,78		-418,52	

Notes: This table presents posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models using a gamma distribution. Values for γ_{1*} to γ_{4*} correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC. * indicates that the estimated parameter is different from 0 with a probability greater than 95%. Negative coefficients imply positive effects on efficiency and the opposite is true for positive coefficients.

Figure 3.A8. Posterior cost and profit efficiency distributions –Gamma vs. exponential inefficiency parameter distributions



Notes: These figures compare posterior cost and profit efficiency distributions for Models C3 and P3, using gamma and exponential distributions.

The Impact of Exogenous Liquidity Shocks on Banks' Funding Costs: Micro-Evidence from the Unsecured Interbank Market

4. The Impact of Exogenous Liquidity Shocks on Banks' Funding Costs: Micro-Evidence from the Unsecured Interbank Market

Abstract

This paper examines the impact of exogenous liquidity shocks in the unsecured interbank market. We evaluate the effects of idiosyncratic liquidity shocks—arising from deposits outflow at the bank level—and of the aggregate liquidity shock related to the U.S. tapering observed in 2013. We find that both liquidity shocks are associated with higher interbank loan prices, albeit the magnitude of the overprice and the impact on the access to interbank liquidity differ depending on the borrower-specific characteristics. More capitalized and liquid banks tend to pay less for liquidity—concurrent with evidence on market discipline—also can absorb better the impact of exogenous liquidity shocks, suggesting benefits from capital and liquidity ratios. Our results suggest that lending relationships can alleviate funding costs during idiosyncratic liquidity shocks, but are less effective during aggregate liquidity shocks, where capitalization, and central bank liquidity have more relevance. Results have implications for both financial stability and monetary policy transmission.

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4.1. Introduction

The unsecured interbank funds market is mainly used by financial institutions to hedge short-term liquidity against idiosyncratic liquidity shocks arising from the behavior of retail depositors (Freixas et al. 2000). Because there is no collateral pledged to the loan, participants in this market have powerful incentives to monitor each other and to maintain stable lending relationships to properly gain access when they face liquidity shocks (Rochet and Tirole, 1996). In normal times, the interbank market tends to be a stable source of short-term funding for banks allowing them to cover idiosyncratic liquidity shocks (Afonso et al. 2014). However, during aggregate liquidity shocks—as observed during the global financial crisis (GFC) of 2008—interbank market liquidity can quickly evaporate due to concerns over counterparty and liquidity risk of its participants (Brunnermeier and Pedersen, 2009; Angelini, et al. 2011; Acharya and Merrouche, 2013), which forced central banks to implement alternative liquidity facilities to alleviate liquidity tensions in the interbank market (Christensen et al. 2009; Allen et al. 2009; Freixas et al. 2011; Abbassi and Linzert, 2012). The unconventional monetary policies implemented in the U.S.—such as the quantitative easing (QE)—and Eurozone to alleviate domestic liquidity tensions have increased global liquidity, leading to capital inflows and easing the financial conditions in emerging markets (Mohanty, 2014; Tillmann, 2016; Anaya et al. 2017). Between May and September, 2013, Fed officials informed the market of the possibility of tapering its securities purchases[1], an unexpected announcement that had negative impact on financial markets in emerging economies, leading to capital outflows, exchange rate depreciation and increased funding costs (Eichengreen and Gupta, 2015; Bouwman et al. 2015; Aizenman et al. 2016).

In this paper, we identify how exogenous liquidity shocks affect borrowing banks in the interbank market. We are particularly interested in understanding these related questions: i) How the availability and pricing of liquidity in the interbank market is affected by exogenous liquidity shocks? ii) Do banks respond differently to an idiosyncratic liquidity shock compared

[1] In early May 2013, Fed officials first began to talk of the possibility of tapering its securities purchases (gradually reducing them from $85 billion monthly to a lower level until its potential termination depending on the US economy conditions). However, in May 22, 2013, the Chairman Ben Bernanke raised the possibility of tapering in his testimony to the Congress, confirming the higher probability to initiate a tapering soon (Bernanke, 2013). The uncertainty related to the QE termination remained until September 17, 2013, when new data on the condition of the US economy led Fed officials to make statements that moderated prior expectations of tapering (Eichengreen and Gupta, 2015).

to an aggregate liquidity shock? iii) Can lending relationships and central bank liquidity mitigate the impact of exogenous liquidity shocks?

Our analytical framework is close to recent studies evaluating the behavior of banks under tight liquidity conditions in interbank markets (Angelini, et al. 2011; Acharya and Merrouche, 2013; Afonso et al., 2014; Bednarek et al. 2015; Braüning and Fecht, 2016). Unlike these studies—that center their analysis on the liquidity shock related to the GFC of 2008 in advanced economies—we focus on the role of market discipline, lending relationships and central bank liquidity in mitigating the impact of idiosyncratic and aggregate liquidity shocks on the interbank market in an emerging economy. We also contribute to this branch of literature by incorporating alternative measures of counterparty and liquidity risk—including bank's stability, banks' liquidity position and liquidity ratios—and by examining the role of reciprocal lending, and secured funding from the central bank and from the money market in alleviating the impact of liquidity shocks in the interbank market.

Our main contribution consists in to evaluate two different types of liquidity shocks. First, because we can observe deposits outflow at the bank level, we use it as an approximation of idiosyncratic liquidity shocks (i.e. bank-specific shocks) that affect both prices and access to the interbank market (Freixas et al. 2000; Aschraft, et al. 2011). Second, we use the U.S. tapering—observed between May and September, 2013—as an aggregate exogenous liquidity shock and evaluate its impact on the interbank market. While most of the literature evaluating the U.S. tapering has focused on its impact using aggregate data at the country level (i.e. exchange rates, capital flows, equity, bonds, CDS, etc.), we use microdata from the interbank market to identity its effect on the availability (and price) of short-term liquidity in an emerging market[2]. To our knowledge, the impact of idiosyncratic liquidity shocks—related to deposits outflow—and aggregate liquidity shocks—associated to the effects of the U.S. tapering—on interbank markets in emerging economies remains unexplored in the literature.

Our analysis uses a rich data set supplied by the CB of Colombia and the Financial Superintendence of Colombia (FSC). First, we use micro-level data on unsecured loans among

[2] See for instance: Rai and Suchanek (2014); Eichengreen and Gupta (2015); Bouwman et al., (2015);Fratzscher, et. al., (2018). In section 5.2 we extend the US tapering period until December 18, to account for the impact of the FOCM meetings on the size of the potential reduction in the QE (Aizenman et. al., 2016).

the financial institutions participating in the Colombian interbank market. Our sample comprises non-publicly available data on daily overnight bilateral unsecured operations among 53 banking institutions from January 2011 to December 2014. The data set also has information of overnight-secured loans in the money market at the bank level. Unique to this paper, we employ observed data on overnight interbank loans instead of approximations of the interest rates and volumes extracted from large-value payment systems.[3] Second, we employ daily liquidity reports including CB' repo operations, deposits, reserve balances, cash holdings, liquid assets, and required reserves of banking institutions, which makes it possible to properly gauge the liquidity position of banks over time. Third, we match these data with bank-specific characteristics of size, risk, capitalization and liquidity using monthly balance sheet reports. The detailed information at the borrower-lender loan level and about lender and borrower specific-characteristics allow us to include a large set of fixed effects in the specifications to control for unobserved heterogeneity, isolate aggregate changes in liquidity, and disentangle supply from demand effects.

Our results contribute to the literature devoted to understand the behavior of the participants in the interbank market and provide new evidence on the effects of liquidity shocks in this market. First, we find that both liquidity shocks are associated to higher liquidity prices and that the overpriced and its impact on the access to interbank liquidity vary with bank-specific characteristics. We observe that, on the one hand, riskier banks pay higher prices and have less access to the market based on the existence of market discipline (Furfine, 2001; King, 2008) and that; on the other hand, these effects are stronger during exogenous liquidity shocks. In addition, large banks are found to pay less for liquidity and have more access to interbank funds—compared to small banks— which concurs with the behavior of surplus banks that exert market power in interbank markets (Allen et al. 1989; Acharya et al, 2012) and with evidence on implicit government guarantees (Angelini et al. 2011). However, we identify that during the US tapering period all banks—irrespective of their size— were affected by higher prices on unsecured interbank loans.

[3] Thus, we can directly observe the characteristics of the interbank loans (i.e., rates, volumes, maturities and counterparties) as they are registered by the participants on a daily basis and reported to the FSC. Therefore, we avoid the disadvantages of the traditional algorithms employed in the literature to extract information on interest rates and the volume of the loans (see, for instance, Furfine 2001; Heijmans, et al. 2010).

Second, we show that although banks facing idiosyncratic liquidity shocks pay higher prices, they are able to obtain funds in the interbank market to cover their liquidity needs by relying more on lending relationships (see, Cocco et al. 2009; Afonso et al. 2014; Braüning and Fecht, 2016). However, the reduction in the loan prices associated to borrowing from lenders with established relationships is lowers for large idiosyncratic shocks, especially for borrowers with less capitalization, suggesting a more significant role of hard information over soft information. We observe that liquid banks—either banks with more stable reserves or higher collateral—can absorb better the impact of idiosyncratic liquidity shocks, highlighting the benefits from liquidity ratios on funding costs.[4] We also find that small banks are more prone to idiosyncratic liquidity shocks, and in turn suffer more in finding liquidity when they face higher credit and liquidity risk (Fecht et al. 2011).

Third, we identify that the U.S. tapering—our aggregate liquidity shock—was associated to increased loan prices in the interbank market and higher volatility in the availability of short-term liquidity. This finding is consistent with the international credit channel suggesting that even if the domestic policy rate remains unaltered (as in Colombia during the US tapering period) domestic financial conditions are affected by the change in monetary policy of the Fed via the role of the dollar as an international currency (Passari and Rey, 2015). Although the higher spread is observed for all banks operating in the interbank market, we identify that the magnitude of the premium varies with the borrower's characteristics. Specifically, less liquid and capitalized banks exhibited higher funding prices and less market access during that period. This result provides micro-evidence on the impact of the U.S. tapering on funding costs in emerging markets, enhancing the scope of the recent literature focused mainly on country level financial and macro data (Eichengreen and Gupta, 2015; Bouwman et al. 2015; Aizenman et al. 2016). Our findings also shed light on the transmission of the U.S. monetary policy to lending conditions in emerging economies (Dias et al, 2017; Morais et al, 2017), which concurs with the spillovers of the global financial cycle (Bruno and Shin, 2015; Rey, 2016).

Fourth, we observe that, unlike idiosyncratic liquidity shocks, lending relationships had lees effect on banks' access to the interbank market during the U.S. tapering, suggesting that hard

[4] Bonner and Eijffinger (2016) show that banks close to their short-term regulatory liquidity requirement pay and charge higher interest rates in the Dutch unsecured interbank market.

information seems to dominate soft information during aggregate liquidity shocks (Bednarek et al. 2015). We find that, in turn, the higher central bank liquidity—which increased by 25% during this period—contributed to mitigate the impact of the U.S. tapering on the interbank market by allowing banks to obtain short-term funding at a large scale. This result not only provides evidence on the crucial role of central banks in alleviating liquidity tensions in the interbank market (Christensen et al. 2009; Allen et al. 2009; Freixas et al. 2011; Abbassi and Linzert, 2012), but also suggests that holding high quality collateral in the banks' portfolios contributes to hedging liquidity risk under aggregate liquidity shocks. We find that reciprocal lending helps banks to smooth the impact of liquidity shocks on its funding costs, which can be related to risk-management motivation, as banks tend to combine deposits and commitment lending to provide a liquidity-risk hedge (see, Kashyap, et al. 2002; Gatev, et al. 2009).

Lastly, our results highlight some benefits from the recent banking regulation. We observe that increased counterparty and liquidity risk is associated with reduced lending activity in the interbank market, evidencing the crucial nexus between counterparty and liquidity risk in unsecured markets (Beltran et al., 2015; Heider et al. 2015). This result implies that capital and liquidity regulatory requirements can contribute to enhance financial stability (Berger and Bouwman, 2013; Pierret, 2015; Calomiris et al. 2015; Bonner and Eijffinger, 2016).

The remainder of this paper is organized as follows. Section 2 provides the background of the Colombian interbank market and shows initial evidence of the impact of exogenous liquidity shocks on the interbank market. Section 3 presents the methodology, and the variables employed in the models' estimation. Section 4 discusses the results. Section 5 presents robustness checks and extensions of the baseline models. Finally, section 6 concludes.

4.2. The interbank market

The Colombian interbank funds market is an unsecured market for liquidity in which participants impose counterparty limits among themselves based on their credit risk assessments[5]. This behavior is of a bilateral (i.e., over-the-counter) nature. Thus, counterparty risk plays a key role in the determination of both the price and the quantity of liquidity that

[5] The credit risk regulation establishes a lending concentration limit of 10% among banks, meaning that a bank is not allowed to have more than 10% of the total lending with a single counterpart.

banks can trade in this market. During the period 2011-2014, approximately 75% of interbank loans were agreed upon at an overnight maturity, demonstrating that it is a short-time market for liquidity. The participants in the interbank market are banking institutions divided into the following categories: commercial banks, financial companies specializing in retail loans and corporate loans for small and medium firms, and financial corporations that operate as investment banks. During the evaluated period, 53 banking institutions participated in the interbank market. Despite the differences in their banking business, these credit institutions usually exchange liquidity among themselves, although large commercial banks tend to be the most active participants, playing the role of super-spreaders of central bank liquidity throughout the interbank market (see León, et al. 2018). As a result, the interbank market rate tends to be close to the CB rate due to it is the target rate for the monetary policy implementation (**Figure 1A**).

4.2.1. Idiosyncratic liquidity shocks

We are interested in understanding the influence of exogenous liquidity shocks on the interbank market. We first evaluate whether borrowing banks suffering deposits outflow (our measure of idiosyncratic liquidity shocks) obtain interbank liquidity at different prices. In **Table 4.1.** we classify all interbank loans granted during 2011-2014 that involve a borrower bank suffering an idiosyncratic liquidity shock (i.e. a deposits outflow) compared to loans in which the borrower does not exhibit such liquidity shock.[6] We observe that loans associated to idiosyncratic liquidity shocks are priced at higher spreads, albeit those loans do not entail grater cross-sectional standard deviations of borrowing rates compared to loans with no liquidity shocks involved. We also observe a higher volume of granted loans, and more lending and borrowing banks, concurrent with the regular activity of the interbank market under idiosyncratic liquidity shocks (Afonso et al. 2014).

In **Table 4.2** we present mean comparison tests of idiosyncratic liquidity shocks and interbank market activity distinguishing between small and large banks. This allows to explore whether idiosyncratic liquidity shocks may affect differently banks depending of their size. In panel A,

[6] In particular, we select all interbank loans of the borrower bank that had a negative rate of change of deposits in t-1 and, 0 otherwise.

we evaluate the frequency and magnitude of idiosyncratic liquidity shocks derived from the behavior of depositors by computing the rate of change in deposits, and the deposits outflow (change and number of days) for participating banks of the interbank market. We classify large (small) banks as those with assets value higher (lower) than the 66th (33th) percentile of the assets distribution during the evaluated period. We observe that large banks tend to have a higher growth of deposits (0.056) compared to small banks (0.011), and that small banks exhibit negative liquidity shocks more frequent than large banks. During the evaluated period, small banks registered a negative rate of growth of deposits for 423 days of the 982 effective days, while large banks exhibit negative liquidity shocks on 327 days, i.e., 43% and 33%, respectively. This seems to be reflected in the distribution of the idiosyncratic liquidity shocks for small and large banks (**Figure 4.1,** panel a), which is consistent with the view that small banks are more affected by liquidity squeezes (Fetch, et al, 2011).

In **Table 4.2** (panel b), we observe that on average, small banks pay 3.0 bps *over* the CB rate for an interbank loan while large banks pay 1.5 bps *under* the CB rate. Indeed, we find a different distribution of borrowing rates between large and small banks (**Figure 4.1,** panel b). We identify ample differences between small and large banks in terms of the amount of funds that they exchange in the interbank market. On average, small banks borrow COP$1.39 billion and lend COP$7.61 billion per day, while large banks borrow COP$16.23 billion and lend COP$7.15 billion. That is, small banks borrow almost ten times less liquidity in the interbank market than large banks, but both lend relatively similar quantities. The implication is that large banks behave as net borrowers in the interbank market while small banks behave more as net lenders (as documented by Allen et al. 1989; Furfine (2001) for the U.S. federal funds market). These findings confirm that small banks are more vulnerable to adverse liquidity shocks and that finding liquidity can be more expensive for those banks compared to large banks (as documented by Fecht et al., 2011).

4.2.2. Aggregate liquidity shocks

Since May of 2013, the announcements from the Fed officials on the possibility of reducing the purchase of assets (i.e. the U.S. tapering) affected negatively financial markets in emerging economies leading to exchange rate depreciation, capital outflows and increased funding costs in emerging markets (Eichengreen and Gupta, 2015; Bouwman et al. 2015; Aizenman et al.

2016; Fratzscher, et. al, 2018) [7]. The impact of this aggregate liquidity shock concurs with the spillovers effects from the U.S. conventional and unconventional monetary policies on emerging markets (see, Rey, 2016; Morais, et al. 2017; Dias et al. 2017) [8]. In Colombia, the U.S. tapering was an aggregate liquidity shock that significantly affected expectations on short-term liquidity, raising concerns among financial authorities (see, Banco de la República, 2013a; Banco de la República, 2013b)[9]. The Colombian government bonds' yields exhibited a rapid increase during the U.S. tapering. The 5-year government' yields (TES) increased from 4.77% in late April to 5.97% at the end of May (i.e. an increase of 120 bps right after the first announcement of the U.S. tapering) and by the end of June, the TES rates achieved 6.84% (i.e. 87 bps more after the second Fed's announcement), following similar trend than the 10-years U.S. Treasury bills (**Figure 4.3A**). In **Figure 4.2**, we observe that the interbank market exhibited higher rates and greater volatility during the U.S. tapering. In the first week of the U.S. tapering announcement (between May 22 and May 30, 2013) the interbank rate exhibited a rapid increase—from 3.12% to 3.26% (i.e. 14 bps or 4.5%)—reaching a level above to the CB rate, and the highest level since the last change of the CB policy rate (i.e. the period between March 27 and May 21, 2013). In the following weeks, the interbank rate exhibited greater volatility, and by the last week of July it again reached a level above the CB rate, followed by a significant decline in the volume of loans from COP 1,000 million to COP 200 million (**Figure 4.2**, right axis), associated to prior expectations from the FOCM meeting of July. During the rest of the U.S. tapering period (i.e. until September 17, 2013) the interbank rate remained above the CB rate, and the volume of loans exhibited greater variation. Note that the spread over the central bank rate continued until mid December, consistent with the last FOCM meeting of 2003 that confirmed the size of the QE reduction from $85 billion per month to $75 billion. **Figure 4.3** and **Figure 4.4** confirm the greater volatility in both interbank market rates and loan volume during the U.S. tapering

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[7] The uncertainty related to the QE termination began in May, 22, 2013 with the Bernanke's speech to the U.S. Congress (Bernanke, 2013) and remained until September, 17, 2013 when the Fed moderated prior expectations of tapering (Eichengreen and Gupta, 2015). Aizenman et. al, (2014) consider that the US tapering uncertainty began in March 20 (with the first announcement of Chair Bernanke to the Congress) and remained until December 18, 2013, when the Fed decided at the FOMC meeting to taper its quantitative easing policy by $10 billion per month, to $75 billion. They also show that financial markets in emerging economies react to both FOMC statements and Fed officials' communications.

[8] Bruno and Shin (2015) show that a contractionary shock to U.S. monetary policy leads to a decrease in cross-border banking capital flows and a decline in the international banks' leverage.

[9] The minutes of the Central Bank of Colombia in May and June mentioned the concerns of the Board members on the financial markets volatility in advanced and emerging markets. In the minutes of June, the Board specifically mentioned that the U.S. tapering has increased the volatility in the international financial markets, which was reflected in a rise in interest rates on Colombian government and private bonds (Banco de la República, 2013b).

period indicating that participants of the interbank market faced higher funding costs and greater uncertainty in accessing the market during the U.S. tapering period.[10]

In response to the weak economic growth and the higher uncertainty in financial markets, the CB of Colombia kept its policy rate unchanged and increased the liquidity supply through the daily repo operations (**Figure 4.1A**) (Banco de la República, 2013b). Between March 26 and May 21, 2013 (before the U.S. tapering) the median daily repo auction was 3.6 billion COP, while during the U.S. tapering it reached 4.5 billion COP (i.e. an increase of 25% in the short-term liquidity granted by the CB) (**Figure 4.4, panel a**). The higher volatility in the interbank market was also reflected in a greater volatility of the banks' reserves holdings accompanied by a slightly increase in the system's excess of reserves (**Figure 4.4, panel b**), which can suggest evidence of liquidity hoarding. The greater liquidity granted by the CB seems to mitigate the transmission of the U.S. tapering to the deposits market as the rate of growth of deposits remained relatively stable and in similar levels to the ones observed during the entire period 2011-2014 (**Figure 4.2A**).

In **Table 4.3,** we present the results of a mean comparison test that allows to identifying whether banks behave differently in the interbank market during the U.S. tapering period. We compare interbank market conditions during the U.S. tapering period and the previous period since the last change of the CB policy rate. We find that during the U.S. tapering the mean loan volume was 13% lower compared to the volume observed the period before. Spite of the interbank rate remained below the CB rate, we observe significantly higher loan spreads and greater volatility of borrowing rates compared to the period before the U.S. tapering. We also identify that during the U.S. tapering there was an increase in the number of borrowing banks and a decline in the number of lending banks. This suggests that the announcement of the U.S. Fed officials related to the possibility to reduce the purchases of assets forced surplus banks to

[10] Unlike other emerging markets and most advanced economies, the interbank market in Colombia has no interconnection with other unsecured interbank markets in the region, including the U.S. The interaction of banks operating in Colombia with banks in other jurisdictions takes place via the cross-border lending market, which is a credit market used for term loans and credit lines with maturities between 3 months to 5 years. Thus, we argue that the transmission of the US tapering in Colombia was observed via increased uncertainty about expected higher interest rates in the U.S. that lead to higher funding costs in the Colombian interbank market (as observed in Figure 2). This is consistent with a potential large-scale capital outflows from emerging markets, after a long period of large capital inflows derived from the lower interest rates and the extraordinary monetary expansion in the U.S. (i.e. the QE) (Mohanty, 2014).

hoard liquidity and in turn, deficit banks had to borrow funds at higher rates. In addition, the wider dispersion across individual borrowing rates during the US tapering period may reflect concerns over counterparty risk across banks, which can be related to uncertainty over the availability of short-term liquidity, which force banks to hoard liquidity for precautionary reasons (see, Diamond and Rajan, 2011; Acharya and Skeie, 2011; Ashcraft et al. 2011; Acharya and Merrouche, 2013).

4.3. The empirical model

The proposed approach relies on the drivers of liquidity demand developed by Heider et al. (2015), in which the decision to borrow—but not the decision to lend—in an unsecured market depends on the banks' own risk, and the market conditions. Thus, our model relates bank-specific characteristics of borrowing banks and market conditions to the prices and availability of funds negotiated in the interbank market. We employ a Heckman-type model to correct for the selection bias in the sample of borrowing banks, which further allows the drivers of bank access to interbank market liquidity to be identified. To achieve identification, we employ a large set of fixed effects that allows to control for unobserved heterogeneity and to disentangle supply from demand effects, as well.

More concretely, because we only observe the interest rate of an interbank loan when it is granted, we need to account for the possibility of a sample selection on unobservable conditions. Thus, we employ a Heckman-type selection model to account for the potential selection bias (Heckman, 1979). This model is proposed because if the bank's decision to participate in the interbank market is non-random, then the estimated coefficients will be inconsistent (Acharya and Merrouche, 2013; Braüning and Fecht, 2016). The model combines a selection mechanism for participating in the interbank market with a regression model.

The selection equation is as follows:

$$z^*_{ijt} = \gamma' w_{ijt} + \mu_{ijt.} \tag{1}$$

The regression model is:

$$p_{ijt} = \beta' X_{ijt} + \varepsilon_{ijt} \tag{2}$$

In (1), z^*_{ijt} is not observed; the variable is observed as:

$$z_{ijt}\begin{cases} 1 \quad if\ z^*_{ijt} > 0 \text{ with Prob}_{(z_{ijt}=1)} = \Phi(\gamma' w_{ijt}) \\ 0 \quad o.w. \quad \text{with Prob}_{(z_{ijt}=0)} = 1 - \Phi(\gamma' w_{ijt}) \end{cases} \tag{3}$$

In the regression model (2), the latent variable p_{ijt} (i.e. the price of the loan) is observed only if $z_{ijt} = 1$, which in our case, indicates that the bank *i* borrows liquidity from bank *j* in the interbank market at time *t*; where X_{ijt} is a vector of variables (i.e. bank-specific characteristics and market conditions) that determine p_{ijt}. The bank's decision to borrowing liquidity is modeled by the selection equation (1), under the mechanism denoted in (3), where w_{ijt} is a set of variables assumed to determine whether z_{ijt} is observed, and ϕ is the standardized normal cumulative distribution function. Therefore, in the selected sample, we have the following:

$$E\,[p_{ijt} \mid z_{ijt} = 1] = \beta' X_{ijt} + \rho\,\sigma_\varepsilon\,\lambda\,(\gamma' w_{ijt}) \tag{4}$$

In (4), λ is the inverse Mills ratio. In addition, $(\mu_{ijt,}\varepsilon_{ijt})$ are assumed to be bivariate normal, with $\mu_{ijt} \sim N(0, 1)$; $\varepsilon_{ijt} \sim N(0, \sigma_\varepsilon)$ and $corr(\mu_{ijt}, \varepsilon_{ijt}) = \rho$. Thus, if $\rho \neq 0$, then standard ordinary least squares (OLS) models applied to (2) will yield biased results. To overcome this problem, we employ a two-step Heckman-type selection model that provides consistent parameter estimates of the second-stage parameters.[11] Under this approach, we first estimate a standard Probit model using equations (1) and (3), then correct for the possible selection bias by including the inverse Mills ratio in the price equations (2) and (4), which are estimated by OLS. Note that in (4), w_{ijt}, is a vector that contains the same set of variables than X_{ijt}, plus an additional variable that validates the Heckman's exclusion restriction.[12] We choose the excess reserves ratio (of both lender and borrower) as our instrument to meet the exclusion restriction under the Heckman two-step procedure (as in Braüning and Fecht, 2016).[13] The rationality is that, under inflation

[11] In order to have borrowing and non-borrowing banks in *t*, we match the bank-specific-characteristics of *all* the banks operating at time *t* with the interbank loan data. Thus, in our matched data, we have banks that are active in the financial system but are not borrowing funds from the interbank market (z=0), compared to banks that are both active and borrowing from the interbank market (z=1) (Braüning and Fecht, 2016).
[12] The Heckman model centers on a valid exclusion restriction: the selection equation should contain at least one variable that is not in the outcome equation. Thus, in (1), we employ an additional variable that conditions the likelihood that a bank will borrow from the interbank market and that is part of w_{ijt}, namely, excess reserves. The excess reserve ratio is defined as the bank's reserve holdings less the amount that a bank needs to hold on a daily basis for the balance of the reserve maintenance period to exactly fulfill the reserve requirements, divided by the average daily required reserves during the month (See Table 4.A3).
[13] That is, the variable should be correlated with the likelihood of a bank to borrow (lend) in the interbank market but has to be less correlated with the interest rate of the loan.

targeting, the central bank uses a corridor to set the short-term interest rate and employs reserve requirements to control for the monetary supply. Thus, one of the main drivers of a bank to borrow from the unsecured interbank market is to fulfill the reserve requirements, and in turn banks with excess reserves also have a greater incentive to lend those funds in this market (Furfine, 2001; Afonso et al, 2014). As the unsecured interbank market is an over-the-counter market (in which participants do not use costly collateral) banks in need of reserves and those with excess of reserves tend to interact more frequent (and at lower costs) compared to the secured market (King, 2008). From a lender's perspective, lend the excess of reserves in the unsecured interbank market at a interest rate slightly higher (or close) to the central bank rate is more profitable than hold the reserves at the central bank at a interest rate of 100 (or 50) bps below the central bank policy rate. From a borrower's perspective, trading liquidity with a counterpart that has excess reserves may entail lower costs and a greater likelihood to get the funds.

We are particularly interested in identifying whether exogenous liquidity shocks can exacerbate concerns over counterparty and liquidity risk, affecting the price and availability of liquidity in interbank markets. Thus, we perform two exercises including the interaction terms of our measures of idiosyncratic and aggregate liquidity shocks with the set of variables in X_{ijt} (and w_{ijt}), which capturing the bank-specific characteristics of the borrower *i*, and market conditions observed at *t*. More specifically, the influence of the idiosyncratic liquidity shock in (4) is identified as:

$$\beta' X_{ijt} (\gamma' w_{ijt}) = \beta_1 * \text{Liquidity\_Shock}_{it} + \beta_2 * \text{Liquidity\_Shock}_{it} \times \text{Borrower\_Characteristics}_{it} + \beta_3 * \text{Liquidity\_Shock}_{it} \times \text{Market Conditions}_t + FE_{ijt} \quad (5)$$

In a similar form, the impact of the aggregate liquidity shock related to the U.S. tapering can be identified as:

$$\beta' X_{ijt} (\gamma' w_{ijt}) = \beta 1 * \text{US Tapering}_t + \beta 2 * \text{US Tapering}_t \times \text{Borrower\_Characteristics}_{it} + \beta 3 * \text{US Tapering}_t \times \text{Market Conditions}_t + FE_{ijt.} \quad (6)$$

Where, $Borrower\_Characteristics_{it}$ includes bank size, counterparty risk measures (i.e. credit risk, capital ratio and z-score), liquidity risk and measures of lending relationships. $Market\ Conditions_t$ is composed of a measure of market liquidity risk and the CB's supply of liquidity. These variables are explained in the data section. In (5), $Liquidity\_Shock_{it}$ denotes an idiosyncratic liquidity shock faced by the borrower bank *i* at time *t* (i.e. deposits outflow), while in (6), $US.\ tapering_t$ corresponds to our aggregate liquidity shock observed during the period *t* in which the Fed announced to the market the possibility of reducing its purchase of assets (between May 22 and September 17, 2013).[14] We saturate the model with a large set of fixed effects (FE_{ijt}) that allow us to control for unobserved heterogeneity and to disentangle supply from demand effects. In particular, we include borrower fixed effects, to control for unobservable bank characteristics of borrowing banks, borrower*lender fixed effects, to account for borrower-lender variation in credit that may affect borrower's participation and loan pricing in the interbank market. We include a set of lender time-variant controls (i.e. size, capitalization, credit risk, and liquidity risk) to control for lender characteristics that may affect the supply of liquidity in the interbank market. We also include lender*time fixed effects to control for variation in supply by lenders in a particular period. Thus, variation in demand of liquidity of a bank from this lender in that period will reflect demand factors as the common supply effect is controlled for. Lastly, we include daily fixed effect to isolating aggregate changes in liquidity.

4.3.1. Variables

We employ a unique data set composed by the universe of overnight-unsecured bilateral loans among the financial institutions participating in the Colombian interbank market. We match the interbank loans with banks' daily liquidity reports (including access to CB repo operations) and monthly banks' balance sheet information to compute bank specific-characteristics related to

[14] In section 5.2 we extend the US tapering period until December 18, 2013 to account for the higher spread over the central bank rate that remained until mid-December, in line with the FOCM of December that informed the market on the size of the reduction in the QE (Aizenman et al, 2016). In Figure 2A, we employ daily data at the bank level and compare the distribution of deposits outflow during the US tapering period (May, 22 to December 18, 2013) and during the full period excluding the US tapering. Although we observe a lower density during the US tapering period, we find that both periods have similar distributions and also both have the same mean value and have similar extreme values. This suggests that there was no increased deposits outflow during the US tapering compared to the full period of study, indicating that the idiosyncratic and aggregate liquidity shocks are orthogonal.

liquidity, credit risk, size, and capitalization. Thus, we construct a daily panel composed of 25,910 unsecured overnight loans granted among 53 financial institutions between January 2011 and December 2014. Summary statistics and definitions of the set of variables employed in the model are presented in **Table 3A** in the appendix.

Our baseline dependent variable in (1) is the match of a borrower bank with a lender bank (i.e. loan), which in case of a successful match ($z_{ijt} = 1$) indicates that the bank *i* borrows liquidity from bank *j* in the interbank market at time *t.* In (2), our dependent variable is the price of liquidity (p_{ijt}), which is defined as the spread in bps between the volume-weighted average interest rate paid by bank *i* to bank *j* over all its overnight unsecured loans during the day (*t*) and the CB rate in *t*. We use the spread to the CB rate because all interbank market participants have access to the regular liquidity of the CB.[15] Thus, p_{it} gauges how costly the liquidity is compared to the CB liquidity. [16]

The main goal of the proposed model is to identify the impact of exogenous liquidity shocks on the price and availability of interbank funds. We employ two alternative liquidity shocks that differ in their nature. First, we use the bank's deposits outflow as our measure of idiosyncratic liquidity shocks, based on that banks suffer from liquidity shocks associated with unexpected withdrawals by their depositors that condition their liquidity (Frexias, et al. 2000; Ashcraft et. al. 2011). Thus, if the bank suffers a deposits outflow in *t-1*, it may force the bank to borrow in *t* from the interbank market and (depending on the bank's characteristics and market conditions) it may entail a greater borrowing cost. In particular, we define the borrower's *liquidity shock*$_{it}$ as a dummy variable equal 1 if the rate of change of the deposits of bank *i* is negative in *t-1* and, 0 otherwise.

Second, we employ the U.S. tapering as an aggregate liquidity shock that may affect the prices of interbank funds as it affected financial conditions in emerging markets (see, Eichengreen and Gupta, 2015; Bouwman et al. 2015). As reported in **Figure 2**, **Figure 3** and **Table 3,** this

[15] All interbank market participants are credit institutions with regular access to central bank liquidity that includes intraday and daily liquidity auctions and overnight liquidity facilities.
[16] To control for the effect of outliers in the estimation, we limit the interest rates to values between -100 bps and 100 bps to the central bank rate. Note also that our pricing measure is given by the spread in bps between the volume-weighted average interest rate paid by bank i to bank j over all its overnight unsecured loans during the day (t) and the CB rate in t. This also helps us to mitigate the impact of outliers (i.e. small loans with a relatively high (or low) interest rate).

announcement was associated with higher volatility in both the price and the availability of interbank funds. We define *US* $tapering_t$ as a dummy variable equal to 1 during the period t in which the Fed announced to the market the possibility of reducing its purchase of assets: between May 22 and September 17, 2013, and 0, during the period immediately before (since the last change of the CB policy rate), that is, between March 23 and May 21, 2013.

As we are particularly interested in identifying the role of counterparty risk in explaining the liquidity prices in the interbank market, we employ alternative measures aimed at capturing counterparty risk of a bank.[17] Initially, we include the ratio of non-performing loans over total loans (*npl*) and the capital ratio (*car*), defined as capital equity (Tier I and Tier II) over risk-weighted assets.[18] We expect that banks with a higher credit risk in their loan portfolios and lower capital ratios pay more for liquidity, given that their creditors tend to charge higher prices to less healthy banks (see Furfine, 2001; King, 2008; Gorton and Metrick, 2012).[19] We compute the bank's *z-score*, which gauges the risk-taking of a bank.[20] This indicator is defined as the sum of the mean rate of the return on assets (ROA) of a bank i (μ_{roa}) and the mean equity-to-assets ratio (*car*) divided by the standard deviation of the ROA σ_{roa}; that is, $z\text{-}score_{it} = (\mu_{roa} + car_{it} / \sigma_{roa})$. It tells us the number of *roa* standard deviations that a bank's ROA must decrease to surpass equity. Thus, a lower z-score indicates a higher probability that a bank will become insolvent, which we expect to be reflected in higher loan prices, suggesting evidence of market discipline.[21] The interaction between our measures of exogenous liquidity shocks and the set of borrower's counterparty risk measures further allows to identifying whether banks approaching insolvency or facing higher credit risk tend to pay more for their liquidity during exogenous liquidity shocks.

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[17] Market discipline considers that if a bank is taking too much risk and its creditors can identify this behavior, then they will request a higher return (i.e., risk premium) that will be reflected in the market prices (Berger, 1991; Flannery, 2001). Evidence on market discipline in financial markets can be found in Sironi (2003); Flannery (2010); Demirgüç-Kunt and Huizinga (2013) and Gurara, et. al., (2018).

[18] Colombian regulation establishes that the capital ratio should be greater than 9%, and it is defined as equity capital over risk-weighted assets plus 100/9 of the value at risk of the bank's securities portfolio.

[19] This is based on the role of peer monitoring given that banks usually have information on the riskiness of their peers and can observe their behavior from different markets (Rochet and Tirole, 1996)

[20] The z-score has been employed as a measure of bank risk-taking in the banking literature (see, for instance, Demirgüç-Kunt and Huizinga, 2010; Bertay et al., 2013).

[21] To compute the z-score, we use the approach of Lepetit and Strobel (2013), in which the mean and standard deviation estimates, μroa_i and σroa_i, are calculated over the full sample [1 … T], and we combine these with the current t values of the equity ratio (car_{it}). Sarmiento et al., (2017) find that banks that consistently pay high borrowing rates in the interbank market exhibit low z-score values, demonstrating their higher riskiness.

We employ several measures of liquidity to gauge the impact of liquidity risk on the price of interbank funds. First, as the liquidity position of banks is affected by the reserve requirements, we expect that banks short on reserves may face liquidity squeezes when approaching the fulfillment date of their reserve requirements, forcing them to borrow funds from the interbank market (Fecht et al. 2011). Thus, to account for the liquidity position of a bank in terms of its reserves holdings, we include a measure of the bank's excess reserves ($excess\_reserves_{it}$). This variable is defined as the bank's reserve holdings less the amount that a bank needs to hold on a daily basis for the balance of the reserve maintenance period to exactly fulfil the reserve requirements, divided by the average daily required reserves during the month. Thus, banks with low (or negative) values in this ratio exhibit a deficit of reserves, and in turn, they are more willing to borrow in the interbank market to fulfil the reserve requirement. This variable is included only in the selection model to account for the Heckman exclusion restriction (Braüning and Fecht, 2016).

Second, we argue that when banks are exposed to relatively large liquidity shocks, they might need to trade funds at unfavorable prices (Cocco et al. 2009). We account for this effect by including a measure of the liquidity risk of a bank *i* at time *t* ($Liquidity\_risk_{it}$), defined as the standard deviation of the daily change in the reserve holdings of the bank during the last 30 days, normalized by the reserve requirements (as in Braüning and Fecht, 2016). In order to evaluate the effect of the bank's structural liquidity on the price and availability of interbank funding, in alternative specifications we employ the ratio of liquid assets to total assets ($Liquidity\_ratio_{it}$). We consider that banks with lower liquidity can be more affected by exogenous liquidity shocks forcing them to borrow funds at higher prices to cover their liquidity needs. We evaluate this prediction by employing a set of interactions between the measures of liquidity risk and our exogenous liquidity shocks.

As we observe in **Table 4.2**, bank size seems to play an important role in liquidity pricing. We control for this effect by including the natural log of the value of a bank's assets ($size_{it}$). We are also interested in testing whether, compared to large banks, small banks are more penalized by their creditors when they face higher liquidity risk and counterparty risk. To account for these effects, we include two interaction terms $small*liq\_risk_{it}$ and $small*npl_{it}$, where small is a dummy variable equal to one if the bank's assets are below the 33th percentile of the assets distribution in the sample and zero otherwise. In addition to this, we interact our exogenous liquidity shocks with the latter set of variables to check whether the concerns over counterparty risk and liquidity risk increased when small banks suffer exogenous liquidity shocks.

Lending relationships play a key role in determining the access of banks to the interbank market. Banks with stable lending relationships benefit from greater access to the interbank market, which contributes to hedging liquidity risk (Cocco et al. 2009; Affinito, 2013; Afonso et al. 2014). To account for this effect, we employ three alternative measures: relationship lending (RL_{ijt}), the borrowing preference index (BPI_{ijt}), and lending reciprocity (RL_rec_{jit}) (Braüning and Fecht, 2016). The *RL* gauges the frequency of interactions between two banks in the interbank market (Furfine, 1999) and is computed by the logarithm of one plus the number of days a bank *i* has lent to bank *j* during the last 30 days preceding day t: $\text{RL}_{ijt} = \log\left(1 + \sum_{t \in T} I(y_{ijt} > 0)\right)$. We expect that banks that keep stable lending relationships have more access to the interbank market and can benefit from lower prices. The BPI_{ijt} is computed as the amount of funds borrowed by bank i from bank j at time t (q_{ijt}) over period T relative to the overall amount borrowed by bank i over the same period T as: $\text{BPI}_{ijt} = \sum_{t \in T} y_{ijt'} / \sum_j \sum_{t' \in T} y_{ijt'}$.[22] Hence, if a bank has higher concentration of counterparties providing liquidity (high *BPI*), it is more likely that it accesses the market on a regular basis to cover its liquidity needs. We consider that a higher frequency and concentration of lending relations may contribute to absorb the impact of idiosyncratic liquidity shocks (as in Afonso, et al. 2014). However, in case of an aggregate liquidity shock, the dependence on a small set of counterparties may lead to higher prices, as all the interbank market participants are being affected by the same liquidity shock (Bernarek, et al. 2015). We also include a measure of lending reciprocity to account for possible mutual insurance against liquidity shocks. The measure is computed as $\text{RL\_rec}_{ijt} = \log\left(1 + \sum_{t \in T} I(y_{jit} > 0)\right)$, which gauge for the number of loans granted from borrower *i* to lender *j* during the last 30 days preceding day *t*. We expect a mitigating effect of reciprocal lending on funding costs of banks affected by liquidity shocks, as banks tend to combine deposits and commitment lending to provide a liquidity-risk hedge (Kashyap, et al. 2002; Gatev, et al. 2009). We check these predictions, by using the interaction of our exogenous liquidity shocks with the lending relationships measures.

[22] We set the variable to zero if the denominator is zero, which means that the banks did not borrow at all. In **Table 4.1A** we present the correlation across the three alternative measures of lending relationships.

Market conditions play a key role in determining the access of banks to the interbank market. In our specification, we include several variables to account for the effects of market conditions. First, we include our measure of liquidity risk; however, it is computed across all banks *j* at time *t*, which corresponds to the standard deviation of the normalized excess reserves among banks, namely, $Market\ Liq\_risk_t$. The intuition here is that in the presence of liquidity imbalances across banks, the liquidity demand tends to increase because more banks need funds, which, in turn, would affect both the prices and volumes in the interbank market. Second, as noted above, all interbank market participants have access to the liquidity of the CB. Thus, we expect that increases in the liquidity supply by the CB might increase the activity of the interbank market and exert downward pressure on interbank prices (León et al. 2018). We account for this effect by including the log of the total liquidity supply of the CB at time *t* ($CB\_Liq\_Supply_t$).[23] We are also interested in testing whether the access to secured money markets alleviates funding costs in the interbank market based on the premise that using collateral reduce borrowing costs (Allen et al. 1989), and on the benefits from diversification across money markets (León and Sarmiento, 2016). To do this, we employ a dummy variable equal to 1 if the bank *i* borrows funds in the secured money market in time *t*, and zero otherwise (Borrowing secured_{it}). Then, we include the interactions of our exogenous liquidity shocks with the set of market conditions to check whether these shocks exacerbate concerns on market liquidity conditions. In **Figure 4**, we observe that during the U.S. tapering the CB significantly increased the liquidity supply, while the volatility of reserve holdings raised suggesting the presence of liquidity imbalances across banks.

4.4. Main Results

4.4.1. The impact of idiosyncratic liquidity shocks in the interbank market

In this section, we present results on the effect of idiosyncratic liquidity shocks in accessing and pricing interbank funds. In **Table 4.4** (panel a), columns (1) to (6), we present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it}=1). In **Table 4.4** (panel b), columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is

[23] The liquidity supply includes the daily liquidity auctions of the central bank (repo operations), intraday repos by demand, and the liquidity facility, which has a penalty rate of 100 bps over the central bank rate.

employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (3) to (6) and (9) to (12) incorporate the effects of our idiosyncratic liquidity shock (deposits outflow) in accessing and pricing funds in the interbank market, respectively. All models have borrower, borrower*lender and time fixed effects to control for unobservable effects of the borrower, borrower-lender availability of credit, and aggregate changes in liquidity, respectively. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). In columns (6) and (12) we check the robustness of our baseline results under a more demanding specification that includes lender*time fixed effects in order to control for variation in supply by lenders in a particular period and thus to capture variation in demand of liquidity (as the common supply effect is controlled for). In addition, we cluster robust standard errors at the borrower bank level.

4.4.1.1. Accessing the interbank market

The specification in **Table 4.4** column (1) includes our set of counterparty risk measures along with the variables of lending relationships and the supply of CB liquidity. This specification allows to identify the impact of counterparty risk of the borrower bank on the access to the interbank market liquidity by controlling for lending relationships and market conditions. Results indicate that banks with higher capital ratios are more likely to borrow liquidity from the interbank market. Interestingly, banks with a higher share of non-performing loans are less likely to borrow from the interbank market. A 1% increase in the share of non-performing loans is associated with 9.1% less probability to borrow from the interbank market. These results confirm that riskier banks have less access to the interbank market (King, 2008, Furfine, 2001). The estimated coefficient of size indicates that the larger the bank, the higher the likelihood that it will borrow from the interbank market. This coincides with our findings in **Table 4.2**, confirming that large banks have incentives to be net borrowers in the interbank market, which can be associated the existence of too-big-to-fail implicit guarantees (Angelini et al. 2011; Davies and Tracey, 2014; Sarmiento and Galán, 2017). We also observe that banks are more likely to obtain funding from a credit bank with whom they had established lending relationships compared to a spot lender, and that the excess of bank's reserves is a key driver of access to the interbank market (Cocco et al. 2009).

In column (2), we include the liquidity position at the bank level (liquidity risk) and across banks (market liquidity risk) to gain further insights into the role of liquidity risk in accessing to the interbank market. We find that banks with a greater liquidity needs are more likely to borrow funds from the interbank market while the opposite is true for banks with excess reserves. The estimated coefficient of *excess reserves*—our additional variable in the selection model—suggests that banks holding large reserves are 12.9% less likely to borrow from the interbank market, while banks facing a higher liquidity risk are 6.3% more likely to borrow liquidity. This result indicates that banks short on reserves or with higher uncertainty over their liquidity needs are more prone to borrowing funds from the interbank market. In addition, we identify that the probability of borrowing liquidity from the interbank market falls 2.7% when liquidity positions across banks are more imbalanced, suggesting lower activity under higher uncertainty over liquidity conditions among banks, which can be associated to precautionary motives (Diamond and Rajan, 2011; Acharya and Skeie, 2011).

In column (3) we include our idiosyncratic liquidity shock (deposits outflow) and interaction terms with bank-specific-characteristics and market conditions. We find that banks facing deposits outflow are 18.1% more likely to borrow liquidity from the interbank market. Interestingly, the estimated coefficient of RL suggests that banks affected by this liquidity shock are 19.6% more likely to get funding from a credit bank with whom they had established lending relationships in the past 30 days, compared to a spot lender[24]. Assuming that the deposits outflow is not caused by bank liquidity reliance, this result confirms the role of lending relationships in overcoming liquidity shocks (Cocco et al. 2009; Braüning and Fecht, 2016). We also observe that—under idiosyncratic liquidity shocks—more capitalized banks are more likely to get funding from the interbank market. In addition, higher CB liquidity supply contributes to overcome the idiosyncratic liquidity shocks faced by borrowing banks in the interbank market. Because of the participants of the interbank market have access to the discount window facility; the latter results may indicate that CB liquidity is used to overcome bank-specific liquidity shocks.

In column (4), we extend the model by including the interactions of liquidity shocks with our measures of liquidity risk, and by including time-variant lender controls. We observe that

[24] The effect is computed as [0.049 x (log(31) – log (1)] + [0.008 x (log(31) – log (1)]=0.1957

greater market liquidity risk significantly reduces the probability of a bank to borrow from the interbank market, suggesting that higher uncertainty over the availability of liquidity may induce liquidity hoarding affecting more those banks with higher liquidity needs. In column (5), we test whether small banks are more affected in accessing the interbank market when facing higher credit and liquidity risk. We find that small banks are more vulnerable to changes in the credit risk exposure as the probability of borrowing funds decreases more compared to large banks (i.e 3.7% vs. 8.3%). Interestingly, we observe that in spite of higher credit risk exposure or liquidity risk do not affect the probability of a small bank to borrow during an idiosyncratic liquidity shocks, those banks have 24.4% less probability of borrowing liquidity compared to a large bank (compare 9.8% vs 16.2%). This may indicate that size plays a crucial role in the access to the interbank market (Furfine, 2001). Lastly, in column (6), we identify that our results are robust to the use of lender*time fixed effects, which suggests that we are capturing how the idiosyncratic liquidity shocks affect the demand for liquidity in the interbank market.

4.4.1.2. Liquidity pricing

After identifying the drivers of a bank to borrow from the interbank market, we estimate the pricing models by using the Heckman second-stage procedure. Results are presented in **Table 4.4** (panel b). The specification in column (7) includes the bank size and the measures of counterparty risk along with the variables of lending relationships and supply of CB liquidity. The results indicate that the price of liquidity decreases with increase in bank size, in line with evidence from the U.S., German, and Portuguese interbank funds markets (see Furfine, 2001; Cocco et al. 2009; Gorton and Metrick, 2012; Abbasi, et al. 2013). We also find that more capitalized banks pay less for liquidity. The estimated coefficient indicates that a 1% increase in the capital ratio (*car*) is associated with a discount on the price of interbank funds of 7 bps. Holding a higher credit risk in the bank's portfolio is associated with higher liquidity prices in the interbank market, suggesting that riskier banks seem to be charged a risk premium (Furfine, 2001). Banks with stable counterparties are associated with a significant lower spread, confirming the importance of lending relationships in interbank markets (see Cocco, et al. 2009; Craig et al. 2015; Braüning and Fecht, 2016). The estimated coefficient of RL has an economic and significant impact: a bank pair that interacted on any given day in the past month will agree on an interest rate that is about 4 bps lower than the spread agreed on a bank pair that did not trade during the prior month.[25] In addition, we observe the higher CB liquidity is associated to lower prices in the interbank market, indicating that CB liquidity can exert downward pressure on market interest rates (Christensen et al. 2009; Allen et al. 2009)

In column (8), we include variables that gauge the liquidity position both at the bank level and across banks to gain further insights into the role of liquidity risk in liquidity pricing. We find that higher volatility of the reserve holdings of borrowing banks is associated with higher loan prices. This effect is captured by our measure of *Liq_risk*, which is significant, although with a relatively small effect. Hence, banks with higher uncertainty over their liquidity needs are associated with higher liquidity prices (Fecht et al. 2011). Liquidity imbalances across banks are associated with higher prices as well. The estimated coefficient of *Market Liq_risk* is positive and highly significant. Note that the estimated coefficient of *Market Liq_risk* (0.065) is considerably larger than that observed at the bank level (0.031). This difference suggests that the price of liquidity in the interbank market is more sensitive to changes in the market liquidity conditions.

In column (9), we include our measure of idiosyncratic liquidity shocks (*Liq. Shock*) and interaction terms with bank-specific-characteristics and market conditions. We find that a deposits outflow force banks to borrow at significant higher prices. On average, a bank facing a deposits outflow in *t-1* pays 5.13 bps more on an interbank loan in *t*, compared to a day in which it has no deposits outflow. Note that the mean spread during the full sample period is 1.85 bps (Table 2A), meaning that the idiosyncratic liquidity shock adds (on average) a premium of almost three times the mean spread in the market.[26] Second, we identify that this liquidity shock seems to have more impact over small and riskier borrowers. The estimated coefficient of the interaction term *Liquidity_shock*size* suggests that large banks pay a lower spread even when they are affected by a deposits outflow. The rationale of this effect can be related to the behavior of smaller banks whose prefer lending to larger banks even at lower rates due to too-big-to-fail considerations (Angelini et al. 2011). Indeed, large banks behave more as net borrowers while small banks as net lender in the interbank market (**Table 4.2**). Deposits

[25] The effect is computed as -1.181 x (log(31) – log (1)=-4.05.

[26] The economic effects are considerable high for the large borrowers that tend to borrow between COP 50,000 million and COP 150,000 million per day (i.e. USD 17,8 million and USD 53,5 million), which can reach up to USD 275,000 and USD 825,200 in a month.

outflow does not affect more the prices of interbank funds for less capitalized banks, but they do increase prices for borrowers with higher credit risk exposition. The estimated coefficient of *Liquidity_shock*npl* indicates that, if a borrower faces a deposits outflow, an increase of 1% in the borrower's share of non-performing loans adds 1.2 bps of spread (an additional 22.2%) compared to a day in which the borrower has no deposits outflow. This finding is consistent with the view that liquidity risk and counterparty risk are intrinsically linked (Heider et al. 2015). Third, we find that lending relationships alleviate borrowing costs for banks suffering idiosyncratic liquidity shocks.

In column (10), we include the interaction terms of our idiosyncratic liquidity shock with measures of liquidity risk, in addition to time-variant lender controls. We find that borrowers facing greater liquidity risk have a significant higher spread associated to deposits outflow. The estimated coefficient of the interaction term *Liq_Shock*Liq_risk* indicates that if a borrower bank faces a deposits outflow, one standard deviation of the ratio between the daily change in the reserve holdings of the bank (during the last 30 days) and the reserve requirements, leads to a premium of 0.8 bps (i.e. 14.3% more compared to the same effect during a day without deposits outflow). During deposits outflow, borrowers' funding costs are more affected by liquidity imbalances across banks as well. The estimated coefficient of the interaction term *Liq_Shock *Market_Liq_risk* suggests that, when the borrower faces a deposits outflow, one standard deviation in the market liquidity risk adds a premium of 1.1 bps, that is 17.4% more compared to a day in which the borrower has no deposits outflow. These results indicate that idiosyncratic liquidity shocks force banks to pay more for their interbank funds when they face greater liquidity risk.

In column (11), we test whether small banks are more penalized by their creditors in the presence of higher credit risk and liquidity risk, and also we check if idiosyncratic liquidity shocks can affect more these banks. The estimated coefficient of interaction of *small*npl* implies that small banks are more sensitive to changes in their credit risk than large banks. Thus, further deterioration in the quality of loans of small banks would have a greater effect on their funding costs in the interbank market. A 1% increase in the ratio of non-performing loans to total loans for small banks is associated with overpricing of 8.8 bps. (i.e. 63,7% higher than the premium for a large bank), which means an extra cost of 117,000 USD over the average loan during a month. Small banks are also more affected by uncertainty over their liquidity needs.

The estimated coefficient of the interaction term *small*liq_risk* is positive and significant. Although the coefficient has a lower level (0.009), the total effect of liquidity risk on small banks is 26.4% higher than that observed for large banks.[27] We also identify that idiosyncratic liquidity shocks have more effect over small banks. When small banks have deposits outflow, they pay 2.39% more for interbank loans compared to large banks, and if an small bank has higher liquidity risk, the overprice is 3.7% more compared to a large bank. This result is consistent with the view that small banks are more affected by liquidity squeezes (Nyborg and Strebulaev, 2004; Fecht, et al. 2011), but also with evidence showing that large banks enjoy lower funding costs in financial markets (Bertay, et al., 2013).

In column (12) we observe that our results are robust to the inclusion of lender*time fixed effects, indicating that we are able to capture the effect of idiosyncratic liquidity shocks on the demand for liquidity in the interbank market. We identify that during a deposits outflow, banks that rely more on lending relationships—compared to spot borrowers—can obtain a lower spread of about 3.83 bps for interbank funds, which is nearly 80% of the observed spread (i.e. 4.87 bps).[28] This finding is in line with Afonso et al. (2014) whose show that in the US Fed funds market, banks pay lower prices and borrow more from their concentrated lenders and that—when there are exogenous shocks to liquidity supply—concentrated lenders insulate borrowers from the shocks without charging significantly higher interest rates.

4.4.2. The impact of the US tapering in the interbank market

In this section, we present results on the impact of our aggregate liquidity shock—related to the U.S. tapering—in accessing and pricing interbank funds as stated in equation (6). The approach is the same as the one employed in evaluating the idiosyncratic liquidity shock. In **Table 5 (panel a)**, columns (1) to (6), we present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel b, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). As in our previous model, all the specifications have borrower,

[27] The total effect of liquidity risk for small banks is computed as follows: $\beta_{liq\_risk} + \beta_{small\ x\ liq\_risk}$ = 0.034 + 0.009 = 0.043. Note that compared to the benchmark group (i.e., large banks), the interaction adds an impact of 26.4% to the effect of liquidity risk.

[28] The effect is computed as [-0.852 x (log(31) – log (1)] + [-0.262 x (log(31) – log (1)]=-3.825.

borrower*lender and time fixed effects to control for unobservable effects of the borrower, borrower-lender availability of credit, and aggregate changes in liquidity, respectively. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). In columns (6) and (12) we check the robustness of our baseline results under a more demanding specification that includes lender*time fixed effects to control for variation in supply by lenders in a particular period and thus to capture variation in demand of liquidity. In addition, we cluster robust standard errors at the borrower bank level.

4.4.2.1. Accessing the interbank market

Results in columns (1) and (2) of **Table 4.5** show that riskier banks have less access to the interbank market, and those that rely more on lending relationships are more likely to borrow funds, as observed during idiosyncratic liquidity shocks. In column (3) we include our aggregate liquidity shock (*U.S. tapering*$_t$) and interaction terms with bank-specific-characteristics and market conditions. We find that during the U.S. tapering the banks were 5.2% more likely to borrow from the interbank market compared to the period before. Note that this probability is considerably lower compared to the one we observe during idiosyncratic liquidity shocks in **Table 4.4** (18.1%), suggesting lower market activity compared to idiosyncratic liquidity shocks. Surprisingly, the interaction terms of banks size and credit risk with the US tapering variable have no significant effect on the probability to access the interbank market, while the effect of capital ratio becomes more relevant. The estimated coefficient suggest that an increase of 1% in the bank's capital ratio is associated with an increase of 8.2% in the probability of a bank to borrow funds in the interbank market. This result may indicate that the U.S. tapering posed more concerns on banks' solvency rather than to their credit risk exposure; and also that large banks faced similar constrains in accessing interbank funds compared to small banks. Another interesting results is that during the U.S tapering, banks that borrowed more from their frequent counterparties had similar access to the interbank market compared to borrowing from spot lenders. This result contrasts to the one we observe under idiosyncratic liquidity shocks, and may suggest that aggregate liquidity shocks do forces liquidity hoarding in the interbank market (Acharya and Merrouche, 2013). Indeed, we observe lower market activity during the US tapering compared to the period before the shock (**Table 4.3**).

In column (4), we identify that banks with higher liquidity risk were less likely to obtain funds during the U.S. tapering, compared to the period before. Note that the opposite effect was found under idiosyncratic liquidity shocks, which may indicate that aggregate liquidity shocks affect more the availability of liquidity compared to idiosyncratic liquidity shocks. During the U.S. tapering, more imbalanced liquidity positions across banks (i.e. higher market liquidity risk) significantly reduce the probability of a bank to borrow from the interbank market. In **Figure 4.4** (panel a) we observe a higher volatility in the banks' reserves holdings around the U.S. tapering period, indicating higher uncertainty over the liquidity conditions during this period. Then, in column (5), we find that small banks are more affected by aggregate liquidity shocks compared to large banks, especially when those banks are less liquid. The probability to borrow funds of a small bank during the U.S. tapering was 16.2% lower compared to the one for a large bank. In addition, an increase in the liquidity risk for small banks further deteriorates the access to the interbank market in 0.02%, which is 18.2% higher compared to large banks. Column (6) confirms that our results are robust to the use of lender*time fixed effects indicating that model is able to identify how the U.S tapering affected the demand for liquidity in the interbank market.

4.4.2.2. Liquidity pricing

Results from the pricing models are presented in **Table 5** (Panel B), columns (7) to (12). The estimated coefficients from the baseline specifications confirm our previous findings on the role of counterparty and liquidity risk in the liquidity pricing in interbank markets. In column (7) we observe that riskier banks are charged with higher prices and that larger banks have cheaper funding from the interbank market, while more liquid banks are associated to lower prices (column 8). In addition, we confirm that lending relations and central bank liquidity alleviate funding costs in the interbank market.

In column (9), we find that the U.S. tapering was associated to significant higher prices in the interbank market. On average, banks paid 3 bps more on an interbank loan, compared to the period before the U.S tapering. Note that this overprice is 61% higher than the mean spread observed during the full period (1.85 bps), albeit lower that the one a bank pay during an idiosyncratic liquidity shock (5.13 bps). Unlike the idiosyncratic liquidity shocks, we observe that the U.S. tapering affected more the prices of interbank funds for less capitalized banks—as well as their access to the market (column 3)—. This indicates that more capitalized banks were able to absorb better the impact of the U.S. tapering, consistent with the role of capital in enhancing the performance of banks during times of increased uncertainty (Berger and Bouwman, 2013).

In spite of the probability to get funds from frequent counterparts during the U.S. tapering was no statistically different from the one to borrow from spot lenders (column 3), results suggest that lending relationships significantly alleviate borrowing costs during aggregate liquidity shocks (Braüning and Fecht, 2016).[29] In addition, higher CB liquidity was associated to lower prices in the interbank market, indicating that CB liquidity can exert downward pressure on market interest rates during aggregate liquidity shocks. This result—in conjunction with the effect of the CB liquidity in the access to interbank market—may indicate that the higher liquidity granted by the CB during the U.S. tapering (which reached 25%, **Figure 4.4**, pane b) contributed to alleviate funding costs in the interbank market and to enhance the access to interbank liquidity (see, Abbassi and Linzert, 2012). This finding is consistent with the evidence of León and Sarmiento (2016), for whom the connective structure of the repo network of the CB can mitigate liquidity tensions in the money market.

In column (10), we find that banks facing higher liquidity risk were charged with a spread of 1.3 bps during the U.S. tapering period. This effect is similar to the one we observe under idiosyncratic liquidity shocks. Interestingly, more imbalanced liquidity positions across banks were associated to a spread of 2.4 bps, which is almost twice the effect associated to the bank-specific liquidity risk. These results indicate that when banks face greater liquidity risk (individual or across banks), aggregate liquidity shocks force them to pay more for their interbank funding. We also observe that banks that rely more on lending relationships—compared to spot borrowers—obtained a lower spread of about 3.6 bps for their interbank funds, which represents 93% of the size of the spread.[30] However, unlike the idiosyncratic shocks, the challenge here is to find a lender due to the probability to get funds from established lenders during the US tapering has no statistical significance (column 4). Note that this

[29] Braüning and Fecht (2016) find that, during the GFC, relationship lenders in the German interbank market provided cheaper loans to their closest borrowers, confirming that lending relationships help banks to reduce search frictions, even for opaque borrowers.

[30] The effect is computed as [-0.876 x (log(31) – log (1)] + [-0.198 x (log(31) – log (1)]=-3.83 bps. This value is 93% of the spread associated to the US tapering (3.94 bps).

specification includes time-variant lender controls to account for supply factors. In column (11), we observe that small banks were more affected by uncertainty over their liquidity needs during the U.S. tapering. The total effect of liquidity risk on small banks was 28.2% higher than that observed for large banks.[31] However, during the U.S. tapering small banks paid only 3.2% more for interbank loans compared to large banks, and under higher liquidity risk, they paid 0.4% more compared to large banks. The lower spread for small borrowers compared to large borrowers and the lack of significance of bank size in the probability to access the interbank liquidity can indicate that the US tapering affected all the banking system. Moreover, the higher effect of the CB liquidity across all the specifications also suggest that the banks' access to the central bank liquidity facilitated the transmission of liquidity to the unsecured market. Note that the baseline results remain intact to the inclusion of lender*time fixed effects, suggesting that the proposed model captures the effect of the U.S. tapering on the demand for liquidity in the interbank market (column 12).

4.5. Robustness and extensions

In this section we perform additional exercises to test the robustness of our baseline results by using alternative bank-specific-characteristics, lending relationships and market access measures. We also investigate the role of lending reciprocity and bank heterogeneity and test our results by using an alternative measures of idiosyncratic liquidity shocks and two sub-periods of the US tapering.

4.5.1. Bank' stability, secured funding and lending concentration

We perform additional exercises to test the robustness of our model by using alternative bank-specific-characteristics, lending relationships and market access measures. First, we test whether the results hold under alternative measures of counterparty and liquidity risk. In particular, we employ the bank's z-score instead of the capital ratio, and employ the ratio of liquid assets to total assets ($liquidity\_ratio_{it}$) as an alternative measure of the liquidity position of the borrower bank.[32] Second, we use a measure of borrowing concentration instead of the

[31] The total effect of liquidity risk for small banks is computed as follows: $\beta_{liq\_risk} + \beta_{small\ x\ liq\_risk} = 0.039 + 0.011 = 0.050$. Note that compared to the benchmark group (i.e., large banks), the interaction adds an impact of 28.2% to the effect of liquidity risk.

[32] Liquid assets include cash holdings, negotiable and available to sell public and private debt instruments and pledged collateral in repurchase agreement operations.

frequency of interactions, by employing the BPI_{ijt} instead of RL_{ijt}. This allows to test whether higher concentration of counterparties providing liquidity (high *BPI*) increases the probability of a bank in accessing the interbank market to cover its liquidity needs. Third, we extend the baseline model in order to test whether the access to secured money markets alleviate funding costs in the interbank market as the use of collateral may reduce borrowing costs (Allen et al., 1989). We employ a dummy variable equal to 1 if the bank *i* borrows funds in the secured money market in time *t*, and zero otherwise ($Borrowing\ secured_{it}$). In addition to check the robustness of our baseline results, this exercise allows assessing the role of banks' stability, liquidity ratios, secured funding and lending concentration in mitigating the impact of idiosyncratic and aggregate liquidity over banks' funding in the interbank market.

The results on the impact of idiosyncratic liquidity shocks in the interbank market using alternative covariates of risk, liquidity, secured funding and lending relationships are presented in **Table 4.6**. Overall, the estimated parameters of the alternative covariates capturing counterparty and liquidity risk yield results similar to those that we obtained in our baseline models. However, they exhibit lower levels but remain significant compared to the estimated coefficients in our baseline specifications. Regarding the z-score, we find that a lower probability of insolvency is associated with more access to the interbank market and lower spread (columns 1 and 6). The estimated coefficient in column (7) suggests that an increase of one standard deviation in the bank's z-score is associated with a decrease in the price of liquidity of 3.2 bps. In addition, we identify that under idiosyncratic liquidity shocks, higher bank's z-score is associated to lower prices (column 9). Thus, banks engaging in less risk-taking are found to pay less for liquidity, confirming our evidence on market discipline.

Banks with a higher ratio of liquid assets are associated with lower prices (column 7), albeit it has no significant impact on the probability to borrow from the interbank market (column 2). However—under idiosyncratic liquidity shocks—, more liquid banks have higher access to interbank market and benefit from lower prices (columns 4 and 10), suggesting that liquid banks are in a better position to obtain liquidity from the money market (Craig et al. 2015). The rationality is that if prices in the unsecured interbank market are high, then banks can use their liquid assets in the secured market to cover their liquidity needs, lowering their funding costs. This intuition is supported by our findings using the indicator variable on the banks' access to the secured money market. We identify that borrowing liquidity in secured markets significantly reduces borrowing costs in the interbank market during idiosyncratic liquidity shocks. This result implies, on the one hand, that collateral can reduce asymmetric information problems (Allen et al., 1989); and on the other hand, that liquid banks (banks with higher collateral) can absorb better the impact of idiosyncratic liquidity shocks[33]. Thus, our results provide further support to the benefits of liquidity ratios in mitigating liquidity shocks, and then in preserving financial stability.

Higher concentration of lending relations (high BPI) is associated to more access to the interbank market (column 1) and lower prices (column 7). In addition, banks with more concentrated counterparties are found to pay lees for liquidity during idiosyncratic liquidity shocks compared to those borrowing from spot lenders (column 9). This effect survives to the use of time-variant lender controls and lender*time fixed effects (columns 10 to 12). The coverage from higher concentration of counterparties ranges between 89% and 93% of the liquidity shock. This result confirms our previous finding using RL, and provides further evidence on the role of lending relationships in mitigating liquidity shocks (Afonso, et al. 2014).

Results on the impact of the aggregate liquidity shock in the interbank market using alternative covariates of risk and lending relationships are presented in **Table 4.7**. We observe similar results to those that we obtained in our baseline models in **Table 4.5**. Regarding the alternative covariates of risk, we identify that during the U.S. tapering, more stable banks are associated to a higher probability to access the interbank market (column 3), and to lower liquidity prices (column 9). More liquid banks are associated to lower interbank loan prices (column 10). We find that higher concentration of counterparties is associated to more access to the interbank market (column 1) and lower prices (column 7). However, during the U.S. tapering, banks that borrow from a small set of counterparties did not obtain significant lower prices (column 9), albeit they did benefit from higher access to the interbank market (column 3). This can be evidence on liquidity hoarding, based on the fact that all the interbank market participants are being affected by the same liquidity shock. Note that in the most demanding specification (columns 6) the estimated coefficient of our measure of US tapering market*liquidity risk is more than three times the one we observe in **Table 4.5** for the interaction of

[33] Bonner and Eijffinger (2016) find that German banks with higher liquidity ratios pay lower prices for their interbank funds. Similarly, Pierret (2015) shows that liquid banks benefit from lower funding costs and a lower insolvency risk

Liquidty_shock*market liquidity risk (compare -0.004 vs. -0.015), and twice in the pricing models (compare 0.011 vs. 0.022). This result implies that during aggregate liquidity shocks, more imbalanced liquidity positions across banks significantly reduced the ability of a bank to borrow funds from the interbank market. Note also that the effect of the CB liquidity remains statistically significant and that the point estimate increases during the U.S. tapering—in line with our previous findings reported in **Table 4.6**—and supporting the role of CB in alleviating liquidity tensions in the interbank market.

Banks with access to the secured market are more likely to borrow from the interbank market, and had more access to the market during the U.S. tapering (column 3). However,—unlike the idiosyncratic liquidity shocks—the higher access to secured market does not significantly reduced borrowing costs; neither contributed to absorb the liquidity shock associated to the U.S. tapering. The lack of significance of secured borrowing in the price models can be associated to the fact that the main collateral used in secured markets is the government bill (TES), which prices were severely affected during the U.S. tapering period (see **Figure 4.3A**, panel b). This lead to increasing funding costs in the secured money market (Banco de la República, 2013). Overall, our results confirm that during aggregate liquidity shocks, in addition to CB liquidity, the role of hard information (solvency and liquidity ratios) seems to be more important in the liquidity pricing than soft information (i.e. lending relationships).

4.5.2. The role of lending reciprocity and bank heterogeneity

Our results suggest that lending relationships are more beneficial in overcoming idiosyncratic liquidity shocks compared to aggregate liquidity shocks. In this section, we test if it holds when there is lending reciprocity that accounts for the possible mutual insurance against liquidity shocks (Braüning and Fecht, 2016). We define $LR\_reciplocal_{ijt}$ as the number of loans granted from borrower i to lender j during the last 30 days preceding day t.[34] We expect that those borrowers suffering a liquidity shock in t-1 are more likely to get funding from banks that have been received funds from the affected banks in the past 30 days[35]. We also check whether there are heterogeneous effects of reciprocal lending depending on bank characteristics. To do this,

[34] The definition of $LR\_reciprocal_{ijt}$ can be found in section 4.3 and Table 4.A2.
[35]This is because of banks tend to combine deposits and commitment lending to provide a liquidity-risk hedge (see, Kashyap, et al, 2002; Gatev, et al. 2009).

we interact our measure of lending reciprocity with the bank's characteristics of size, capital ratio and liquidity risk. We employ a similar specification than in eq. 5 for the idiosyncratic liquidity shocks and as in eq. 6 for the effect of the US tapering. We include a large set of fixed effects including borrower, borrower*lender, lender*time, and time fixed effects, in addition to time-variant lender controls.

We use the size of the idiosyncratic liquidity shock to test whether the shocks are related to public information about the banks' riskiness (i.e. endogenous) or to depositors' preferences (i.e. more exogenous). Large shocks can be more related to public information on the bank's behavior, while small shocks can be related to a rebalancing of deposits (across banks) or to the depositors' liquidity needs (Freixas et al. 2011). In **Figure 4.1** (panel a) we observe that while most of the banks' deposits outflow is within a range of {-3,0} standard deviations, some shocks reached up to -8 standard deviations. This suggests that in our sample some banks exhibited large liquidity shocks. To test these predictions, we estimate the model using a subsample of interbank loans composed only for those loans in which the borrower banks exhibited a deposits outflow, and then redefine the liquidity shock equal to 1 for those loans in which the borrower has a deposits outflow in t-1 *greater* than the mean deposits outflow observed in t-1 (i.e. large shock) and zero for those interbank loans for which the deposits outflow of the borrower in t-1 was *lower* than the mean deposits outflow in t-1 (i.e. small shocks).

Results are presented in **Table 4.8**. Columns (1) to (3) and (6) to (8) are the probability and price models using the baseline definition of liquidity shock and the full sample, while columns (4) to (5) and (9) to (10) are the results of the probability and price models using the sample with only interbank loans affected by deposits outflow, and the indicator variable of liquidity shock comparing between large and small liquidity shocks as defined above. We observe that banks that have a reciprocal lending relationship tend to have higher access to the interbank market (column 1) and that it also helps them to overcome the effect of idiosyncratic liquidity shocks (column 2). In column (3), we identify that large banks and those with higher capital ratio benefit more from reciprocal lending during idiosyncratic liquidity shocks as they are associated to higher access to the interbank market. Results from the price models show that banks that rely more on reciprocal lending benefit from significant lower interbank prices (column 6), and that they also are able to cover—*ceteris paribus*—around 86% of the overprice observed during idiosyncratic liquidity shocks (column 7).[36] Moreover, large and more capitalized banks benefit more from reciprocal lending during idiosyncratic liquidity shocks, albeit the effect is relatively small (0.005 and 0.002, respectively). The observed effects of the CB liquidity and the risk covariates remain as in our baseline models.

We identify that banks affected by relatively large idiosyncratic liquidity shocks are more sensible to its capitalization level and to the market liquidity risk. Also those banks seem to depend less on reciprocal lending compared to banks affected by small liquidity shocks (columns 4 and 9). The higher sensitivity to market liquidity risk—in terms of both access and prices—may indicate that it can be more difficult for a bank suffering a large liquidity shock to find enough funds in the interbank market when there is higher uncertainty in the market (i.e. higher volatility in the excess of reserves across banks). Our interpretation of the result on the lower effect of lending reciprocity is that when banks need to cover large liquidity shocks they try to borrow from both known counterparts and spot lenders to diversify its exposition to its main lenders, as they have private information gained by repeated interaction in the interbank market. Note that the reduction in the spread for banks with reciprocal lending is only 65%, which is 21 percentage points lower compared to the baseline in column (7). Moreover, the fact that capitalization is associated to higher access to interbank liquidity— and to significant lower prices (column 10)—indicate that large shocks can affect more the weaker banks, and that public information on the borrower' solvency has a crucial effect on the banks' funding costs (Furfine, 2001; King, 2008). Indeed, the estimated coefficient of the interaction term Liquidity Shock*LR_reciprocal*Capital_ratio suggests that banks with higher capital ratios benefit more (i.e. higher access and lower prices) from their reciprocal relations when they are facing large liquidity shocks, compared to banks facing small shocks (columns 5 and 10). Overall, the results indicate that banks exhibiting large liquidity shocks are more penalized by their counterparts compared to those banks suffering small liquidity shocks, and that market characteristics and hard information becomes more relevant in determining the access and pricing of interbank liquidity under large liquidity shocks. This confirms that large shocks can be more associated to public information on the banks' behavior, while small shocks can be

[36] The effect is computed as [-0.835 x (log(31) – log (1)] + [-0.321 x (log(31) – log (1)]=-3.970 bps. This value represents 86% of the spread associated to the idiosyncratic liquidity shock (i.e. 4.626 bps).

related to a rebalancing of deposits (across banks) or to the depositors' liquidity needs (Freixas et al, 2011).

In **Table 4.9** we present the results of the role of lending reciprocity and bank heterogeneity during the US tapering in order to test whether reciprocal relationships might contribute to smooth the impact of aggregate liquidity shocks in the interbank market. In addition to this, we also test our results by using an alternative measure of the US tapering period. **Figure 4.2** shows that the interbank rate in Colombia reached a level above the central bank rate on May 22 (in line with Bernanke's testimony), and then exhibited higher volatility until mid-July when it reached again a level above the central bank policy rate (coinciding with prior expectations on the FOMC of July). The spread over the central bank rate remained until mid December, in line with the FOCM of December that informed the market on the size of the reduction in the QE[37] (as documented by Aizenman et. al. 2014). This suggests that the uncertainty derived from the US tapering may have affected the interbank market in Colombia between May and December, but also that there are two different periods during the tapering: i) high volatility—from May, 22 to July, 30—, and ii) high prices—from July, 31 to December, 18—.[38] To account for these sub-periods under our analytical framework, we split the sample and redefine the US tapering variable. In particular, we use a first sample for the period March 26 to July 30, and then define the US Tapering variable as equal 1 during May 22 to July 30 (i.e. beginning of the tapering), and 0 during March 26 to May 21 (i.e. before the tapering). Then, we use a sample for the period May 22 to December 18—corresponding to the extended US tapering—, and define the US Tapering variable equal to 1 for the period July 31 to Dec 18 (i.e. high loan prices), and 0 for the beginning of the tapering—May 22 to July 30—in which we observe higher uncertainty in the interbank market.

In columns (1) to (3) and (8) to (10) we present the results of the probability and pricing models, respectively, using the baseline sample and the initial definition of the US tapering. We

[37] Our definition of the tapering period follows Eichengreen and Gupta (2015) whose identify the beginning of the tapering in May 22, 2013 until September 17, 2013. Aizenman et. al, (2014) consider that the US tapering uncertainty began in March 20 (with the first announcement of Chair Bernanke to the Congress) and remained until December 18, 2013, when the Fed decided at the FOMC meeting to taper the QE by $10 billion per month, to $75 billion. They also show that financial markets in emerging economies react to both FOMC statements and Fed officials' communications.

[38] Figure 3 (panel b) confirms that there was an increased volatility on interbank' loan volume between May and July and then a decline in the loan volume until December.

find that most of the estimated effects remain as in our baseline model. Banks that rely on lending reciprocity are found to have higher probability to access the interbank market (column 1) and also benefit from lower prices (column 8). However, when we evaluate the effect of reciprocal lending during the US tapering we observe that the price reduction declined from 92% in the baseline (column 9) to 79% in the sub-period of tapering uncertainty (column 11), and then to 64% in the sub-period of high prices (column 13). This result reflects not only the increased liquidity prices during the US tapering, but also could indicate that banks in need of liquidity were forced to trade with spot lenders at higher prices. We also observe that more capitalized banks were able to get funding at lower prices during the US tapering, and also during the sub-periods of increased uncertainty and high prices of the US tapering. The benefits of higher capitalization are also observed from borrowers that obtained funding from reciprocal lenders (column 14). Note that bank size is associated to lower prices during the US tapering (baseline) but then it is no longer significant during the sub-periods of US tapering uncertainty and high prices, and also when we interact it with reciprocal lending. This finding confirms that all banks—irrespective of its size—were affected by higher liquidity prices during the US tapering. Indeed, we observe a higher effect of the market liquidity risk during the sub-periods of uncertainty and high prices compared to the baseline period.

4.6. Final remarks

This paper evaluates the impact of liquidity shocks on the behavior of banks participating in the interbank market. We study the impact of idiosyncratic liquidity shocks—associated to deposits outflow at the bank level—and of the aggregate liquidity shock derived from the US tapering—observed between May and September, 2013—on the access and pricing of interbank liquidity. Our results indicate that both liquidity shocks are associated with higher interbank loan prices, albeit the magnitude of the overprice and the impact on the access to interbank liquidity differ depending on the borrower-specific characteristics. In particular, riskier banks are found to pay higher prices and to have less access to the market confirming evidence on market discipline. Moreover, we observe that these effects are stronger during exogenous liquidity shocks. One implication of our results is that higher capital and liquidity buffers can reduce short-term funding costs, and increase access to interbank market liquidity, allowing banks to absorb better the impact of exogenous liquidity shocks. Thus, recent regulation—under the umbrella of Basel II and III—can contribute to mitigate the impact of exogenous liquidity shocks over short-term funding.

Our findings on the impact of the U.S. tapering in the Colombian interbank market are consistent with the international credit channel in which domestic financial conditions are affected by the change in the U.S monetary policy via the role of the dollar as an international currency. We also identify that during aggregate liquidity shocks, the role of the central bank in alleviating liquidity strains throughout the interbank market becomes more relevant—as hard information seems to dominate soft information—while the benefits of lending relationships are significantly more important when banks face idiosyncratic liquidity shocks. Overall, our results point out that understanding the impact of exogenous liquidity shocks on the interbank market is crucial for identifying potential disruptions in the allocation of liquidity that could affect not only short-term funding, but also bank lending and monetary policy transmission.

Table 4.1. The impact of idiosyncratic liquidity shocks on the interbank market.

Interbank market conditions	Liquidity shock = 0	Liquidity shock =1	Difference
No of loans	35,56	41,24	-5,68***
Total volume of loans	532.240	603.340	-71.100***
Average amount of loans	11.635	14.723	-30.88***
Average spread of loans	0,03	0,07	-0,04***
Spread to CB rate	0,05	0,07	-0,02
St. Dev of spreads of loans	0,05	0,06	-0,01
No. of lending banks	22,12	23,45	-1,33
No. of borrowing banks	17,71	21,35	-3,64***

Notes: This table presents mean comparison test for daily variables of the interbank market. Liquidity shock =1 corresponds to all interbank loans that involve a borrower bank suffering an idiosyncratic liquidity shock (i.e. a deposits outflow). Liquidity shock=0 is composed by the remaining loans in which the borrower does not face this liquidity shock. The test employs all loans observed between January 1, 2011 and December 30, 2014.*** p>0.01

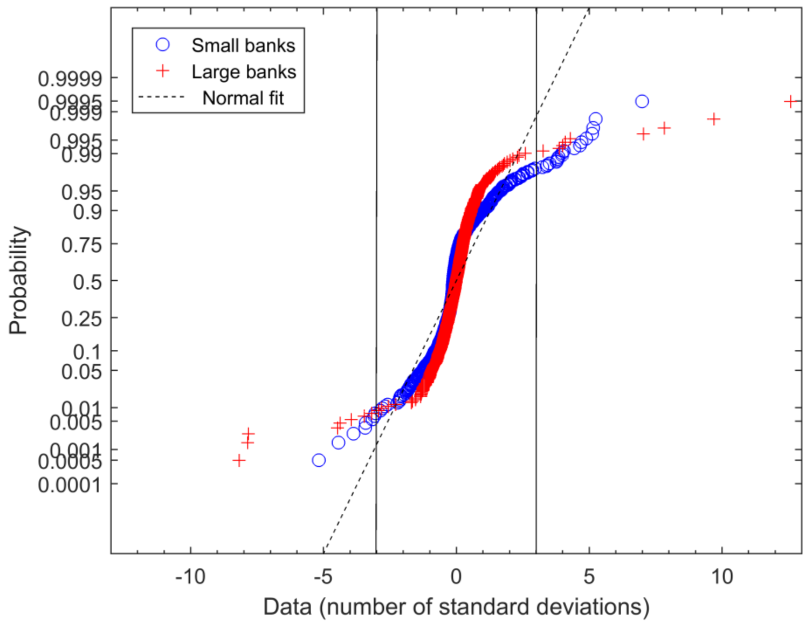
Table 4.2. Banks' size, idiosyncratic liquidity shocks and interbank market activity

Idiosyncratic liquidity shocks (Panel a)	Small banks	Large banks	Difference between large and small banks
Change in deposits (percent)	0,011	0,056	0,045***
Deposits outflow (percent)	-0,137	-0,084	0,053***
Deposits outflow (No of days)	423	327	-96***
Interbank market activity (*Panel b*)			
Spread (bps)	3,00	-1,50	-4,50***
Total amount borrowed (billion COP)	1,39	16,28	14,89***
Total amount lent (billion COP)	7,61	7,15	-0,47***
Net position	6,22	-9,13	-15,35***

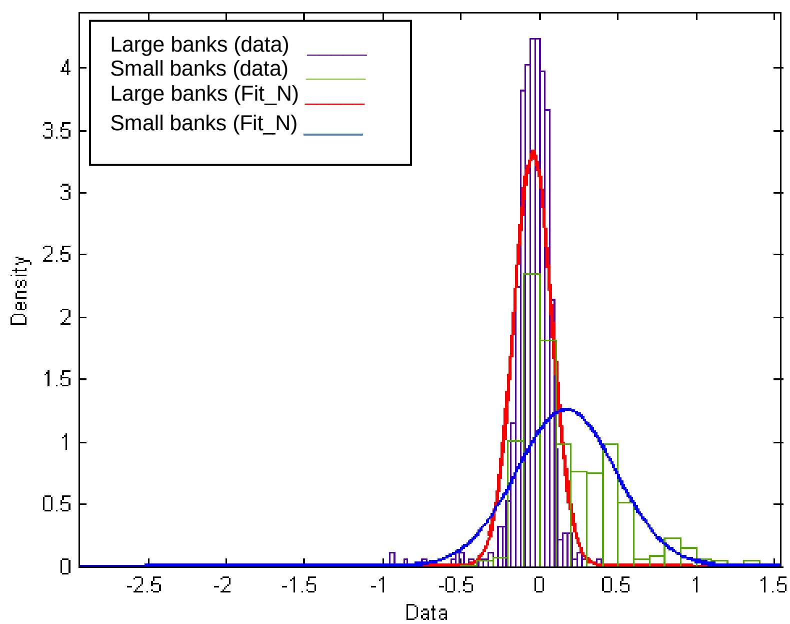
Notes: This table presents mean comparison tests for selected variables of participating banks in the interbank market. Large (small) banks are those with assets value larger (lower) than the 66th (33th) percentile of the assets distribution during the period. In Panel A change in deposits is the daily mean change in the deposits of the bank (in percent). Deposits outflow is the mean value of the negative rate of change in deposits (percent), and the number of days a bank has a negative rate of change of deposits. Panel B has measures of interbank market activity. Spread is the difference between the interest rate paid by a bank in the interbank market and the CB rate measured in basis points (bps). Total amount borrowed and total amount lent in the interbank market per day in billion COP. Net position is the difference between the total amount lent and the total amount borrowed during a day in billion COP. *** p>0.01

Figure 4.1. Idiosyncratic liquidity shocks, banks' size, and borrowing costs

Panel (a) Distribution of idiosyncratic liquidity shocks by banks' size

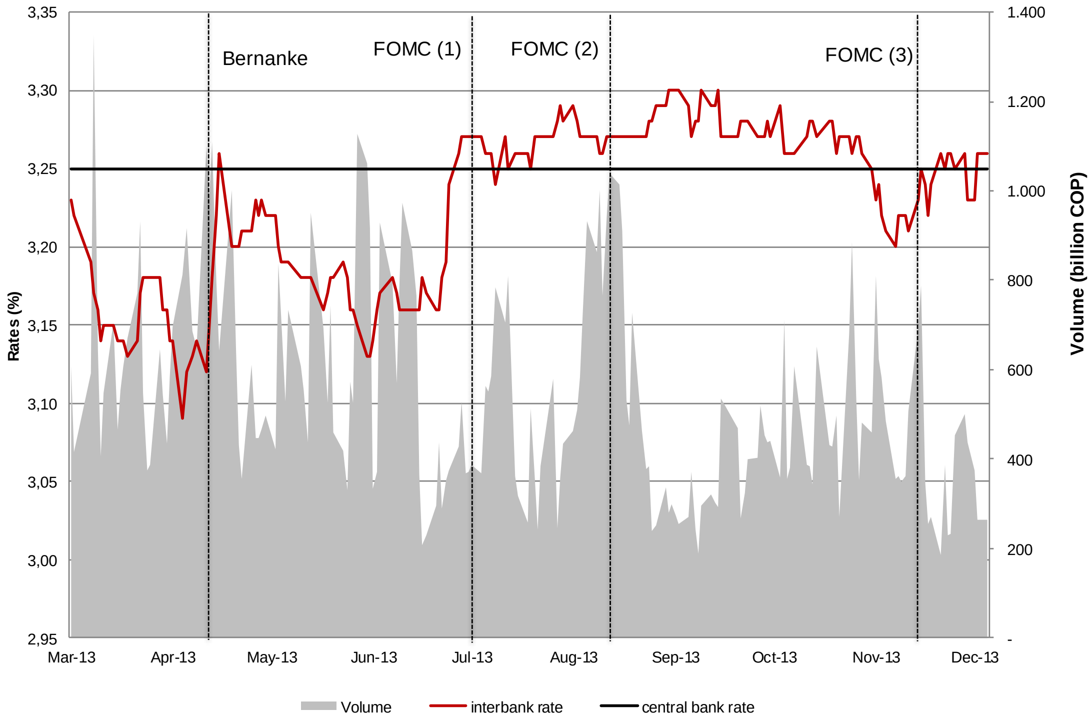


Panel (b) Distribution of borrowing rates by banks' size



Notes: Panel (a) presents the distribution of the rate of change of deposits by type of bank during the period 2011-2014 assuming normal distributions. Panel (b) presents the distribution of the interest rates of overnight-unsecured loans in the interbank market during the period 2011-2014. In both figures large (small) banks are those with assets value larger (lower) than the 66th (33th) percentile of the assets distribution during the period.

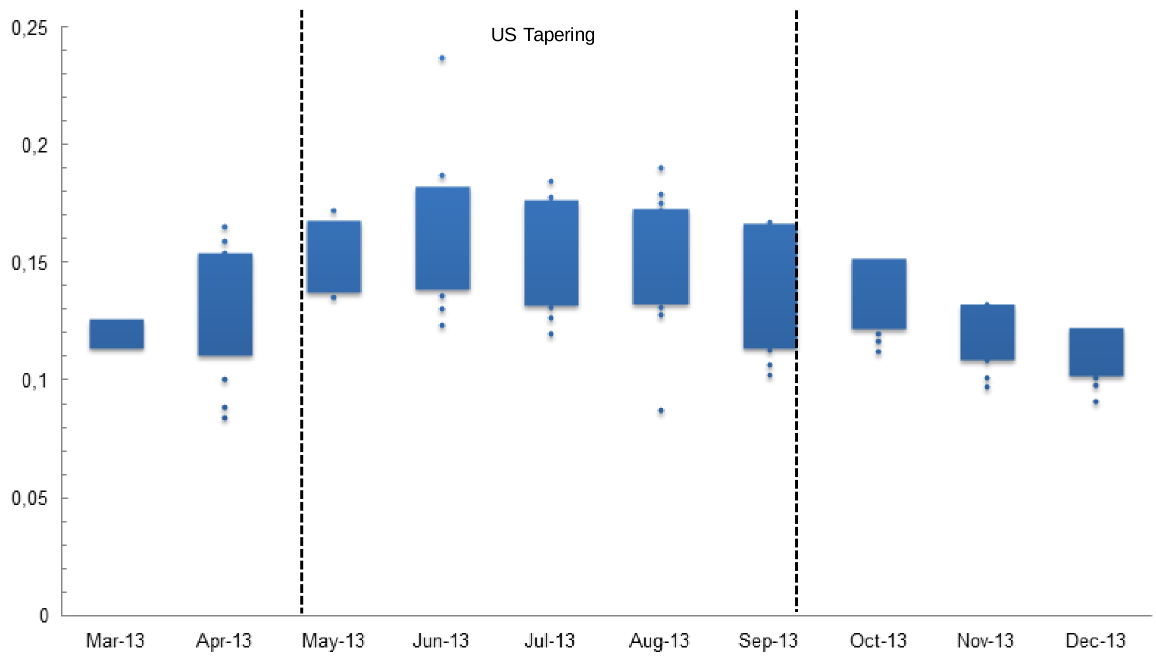
Figure 4.2. The impact of the U.S. tapering in the Colombian interbank market



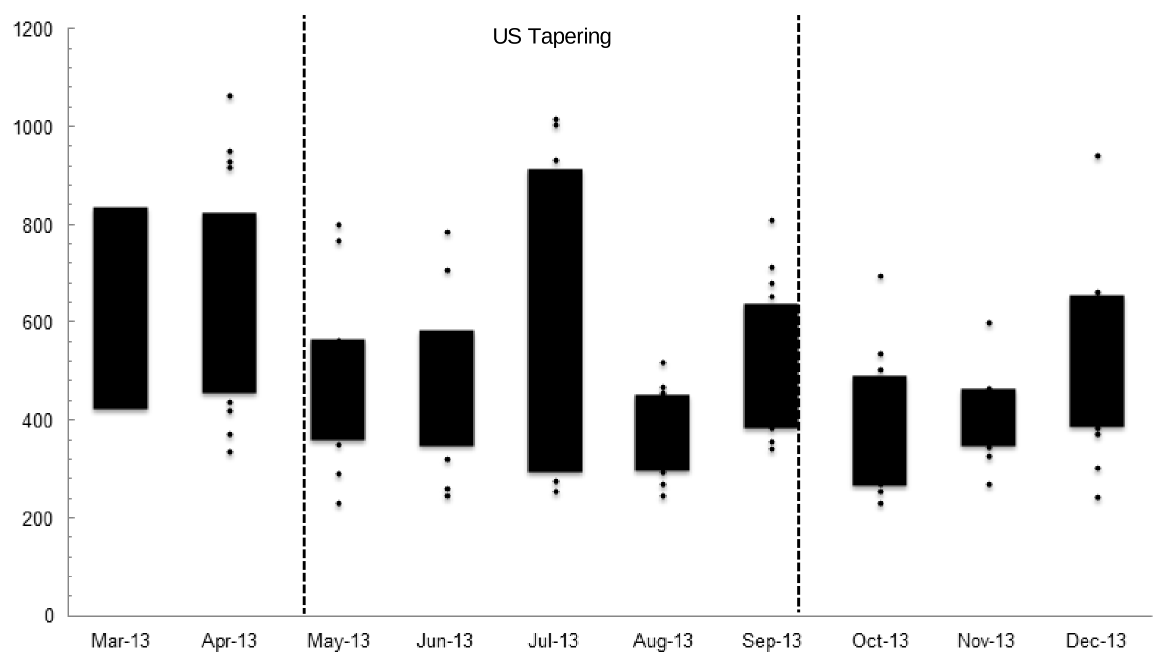
Notes: This figure depicts the overnight interbank market rate (red line) and central bank rate (black line) in percentage (%) during the period March 26 and December 30, 2013. Average daily amount traded in the interbank market in billion COP (Right axis). Dotted lines correspond to the U.S. tapering announcements: Bernanke's speech to the Congress (May, 22), FOMC (1) is from July, 31, FOMC (2) from September 17, and FOMC (3) from December 18.

Figure 4.3. Interbank market volatility during the U.S. tapering

Panel (a) Volatility of the interbank market rates



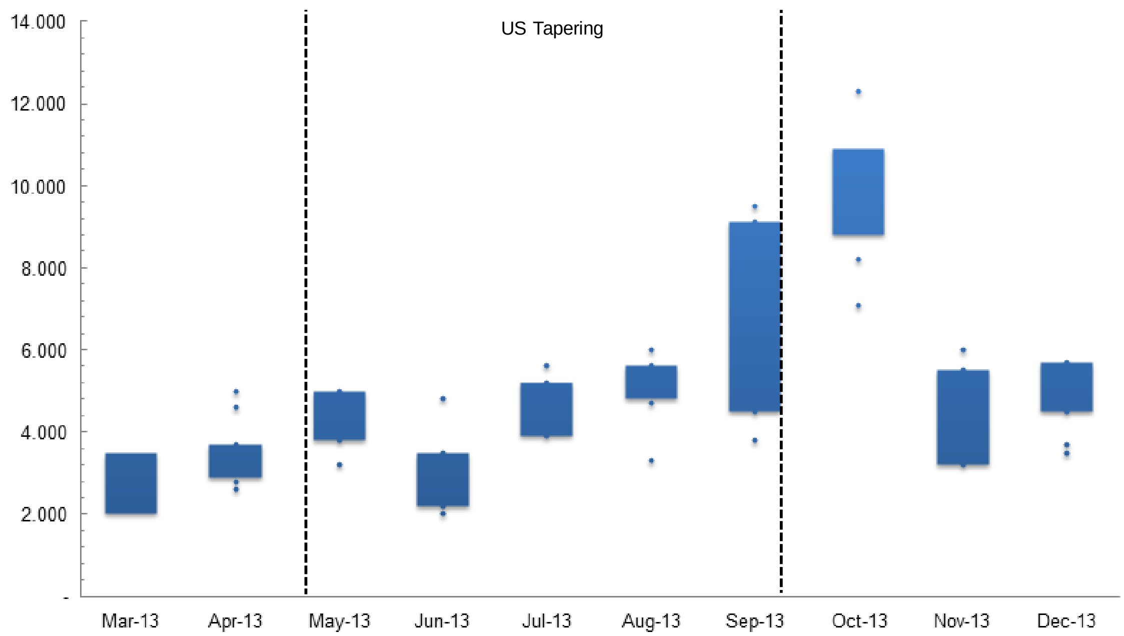
Panel (b) Loan volume in the interbank market



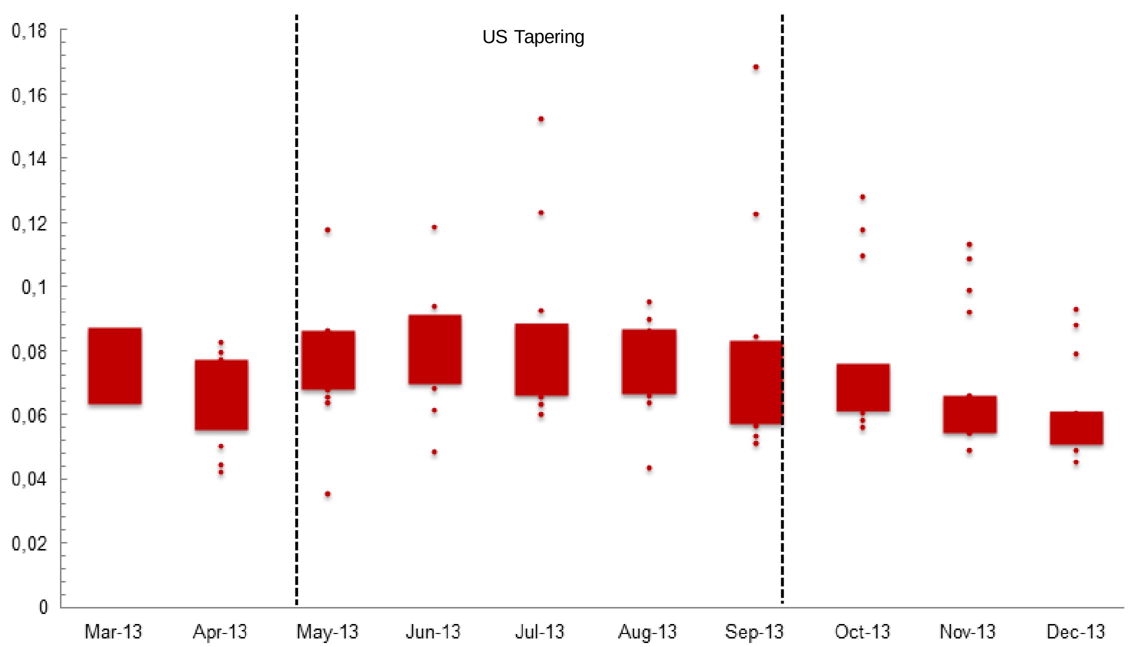
Notes: Panel (a) depicts the standard deviation of the overnight interbank market rate in percentage points. Panel (b) presents the daily volume of interbank loans (billion COP). Data is from the period March 26 and December 30, 2013. Dotted lines correspond to the U.S. tapering period: May 22 to September 17, 2013.

Figure 4.4. Market liquidity and the U.S. tapering

Panel (a) Central bank liquidity supply



Panel (b) Volatility of banks' reserve holdings



Notes: Panel (a) shows the CB liquidity supply (i.e. size of the REPO auction on a daily basis in billion COP). Panel (b) depicts our measure of market liquidity risk defined as the standard deviation of the normalized excess reserves across banks (per day) in percentage points. Data is from the period March 26 and December 30, 2013. Dotted lines correspond to the U.S. tapering period: May 22 to September 17, 2013.

Table 4.3. The impact of the U.S. tapering in the Colombian interbank market

Interbank market conditions	U.S Tapering =0	U.S Tapering =1	Difference
No of loans	40,23	37,25	-2,98***
Total volume of loans	666,57	579,55	(87,02)***
Average amount of loans	12.356	10.503	(1.853)***
Average spread of loans	0,04	0,07	0,03***
Spread to CB rate	-0,03	0,02	0,05***
Std of spreads of loans	0,04	0,14	0,10***
No. of lending banks	21,47	20,12	-1,35
No. of borrowing banks	16,46	19,76	3,30***

Notes: This table presents mean comparison test for daily variables of the interbank market. U.S Tapering =1 corresponds to the loans granted during May 22 and September 17, 2013, while U.S Tapering =0 covers the loans granted between March 27 and May 21, 2013. Amount in COP million and spread is the difference (in percentage points) to the CB rate. *** p>0.01.

Table 4.4. The impact of idiosyncratic liquidity shocks in the interbank market

Variables	Panel A: Probability to access the market: P (zit =1)						Panel B: Pricing Models: Spread it					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidity Shock$_{it-1}$			0,181	0,162	0,131	0,119			5,135	5,356	5,267	4,872
			(5,87)***	(5,60)***	(5,81)***	(5,23)***			(5,30)***	(5,29)***	(5,91)***	(6,18)***
Size$_{it}$ [Log of assets (mln)]	0,130	0,139	0,121	0,135	0,122	0,127	-0,110	-0,108	-0,112	-0,117	-0,116	-0,123
	(4,06)***	(4,02)***	(3,76)***	(4,04)***	(3,55)***	(3,42)***	(-3,12)***	(-3,23)***	(-2,81)**	(-2,74)**	(-3,12)***	(-3,31)***
Capital ratio$_{it}$ (percent)	0,051	0,064	0,052	0,057	0,053	0,056	-0,069	-0,071	-0,064	-0,074	-0,061	-0,047
	(3,21)***	(3,11)***	(3,02)***	(3,42)***	(3,46)***	(3,34)***	(-1,79)*	(2,46)**	(2,31)**	(2,53)**	(2,27)**	(2,09)**
Npl$_{it}$ (percent)	-0,091	-0,082	-0,095	-0,079	-0,084	-0,079	0,052	0,051	0,054	0,059	0,063	0,071
	(-1,86)**	(-1,81)**	(-1,76)*	(-2,09)**	(-2,15)**	(-1,48)	(2,46)**	(2,59)**	(2,61)**	(2,16)**	(2,19)**	(2,38)**
Liquidity_risk$_{it}$ (percent)		0,063	0,061	0,072	0,069	0,073		0,031	0,037	0,047	0,034	0,027
		(2,19)**	(2,11)**	(2,08)**	(2,16)**	(2,20)**		(3,19)***	(3,25)***	(4,04)***	(3,17)***	(3,40)***
Market Liq_risk$_{t}$ (percent)		-0,027	-0,038	-0,017	-0,024	-0,019		0,065	0,071	0,061	0,072	0,064
		(-1,87)**	(-1,82)**	(-1,79)*	(-1,83)*	(-1,75)*		(3,87)***	(3,91)***	(3,23)***	(2,28)**	(2,53)**
Liquidity Shock$_{it-1}$ * Size$_{it}$ [Log of assets (mln)]			0,005	0,007					-0,019	-0,017		
			(1,67)*	(1,42)					(-1,91)*	(-1,93)*		
Liquidity Shock$_{it-1}$ * Capital ratio$_{it}$ (percent)			0,061	0,057					-0,004	-0,007		
			(2,47)**	(2,41)**					(-1,19)	(-1,27)		
Liquidity Shock$_{it-1}$ * Npl$_{it}$ (percent)			-0,016	-0,018	-0,011	-0,007			0,012	0,011	0,007	0,014
			(-1,19)	(-1,22)	(-1,16)	(-1,19)			(2,19)**	(2,34)**	(2,33)**	(2,75)**
Liquidity Shock$_{it-1}$ * Liquidity_risk$_{it}$ (percent)				-0,011	-0,008	-0,015				0,008	0,013	0,012
				(-1,08)	(-1,05)	(-1,14)				(3,19)***	(3,73)***	(3,30)***
Liquidity Shock$_{it-1}$ * Market Liq_risk$_{t}$ (percent)				-0,008	-0,009	-0,012				0,011	0,008	0,009
				(-1,95)**	(-2,11)**	(-2,26)**				(2,95)***	(2,70)**	(1,89)*
Small$_{it}$ * npl$_{it}$ (percent)					-0,046	-0,053					0,025	0,029
					(-2,55)**	(-2,38)**					(2,71)**	(2,63)**
Small$_{it}$ * Liquidity_risk$_{it}$ (percent)					0,004	0,003					0,009	0,011
					(1,47)	(1,23)					(2,34)**	(2,80)**
Liquidity Shock$_{it-1}$ * Small$_{it}$					-0,033	-0,041					0,126	0,119
					(-4,11)***	(-3,34)***					(2,75)***	(3,14)***
Liquidity Shock$_{it-1}$ * Small$_{it}$ * npl$_{it}$ (percent)					-0,018	-0,007					0,071	0,073
					(-1,34)	(-1,28)					(1,09)	(1,13)
Liquidity Shock$_{it-1}$ * Small$_{it}$ * Liquidity_risk$_{it}$ (percent)					-0,003	-0,005					0,033	0,028
					(-1,23)	(-1,25)					(2,16)**	(2,32)**
RL$_{ijt}$	0,048	0,051	0,049	0,041	0,042	0,045	-1,181	-1,192	-1,167	-0,948	-0,874	-0,852
	(7,59)***	(6,21)***	(7,04)***	(6,82)***	(6,70)***	(5,28)***	(-5,59)***	(-5,10)***	(-4,38)***	(-4,19)***	(-3,31)***	(-3,62)***
Liquidity Shock$_{it-1}$ * RL$_{ijt}$			0,008	0,012	0,013	0,017			-0,411	-0,372	-0,331	-0,262
			(2,59)***	(2,86)***	(3,17)***	(3,41)***			(-3,84)***	(-3,18)***	(-2,97)***	(-3,21)***
CB Liq_supply$_{t}$ [ln (mln)]	0,012	0,015	0,022	0,018	0,015	0,011	-0,038	-0,027	-0,021	-0,022	-0,027	-0,033
	(1,28)	(1,25)	(1,18)	(1,09)	(1,43)	(1,23)	(-1,72)*	(-1,84)*	(-2,03)**	(-2,19)**	(-2,35)**	(-1,78)*
Liquidity Shock$_{it-1}$ * CB Liq_supply$_{t}$ [ln (mln)]			0,004	0,005	0,006	0,003			-0,008	-0,004	-0,006	-0,003
			(1,25)	(1,33)	(1,23)	(1,15)			(-1,25)	(-1,76)	(-0,97)	(-1,06)
Inv_Mills ratio$_{it}$							-4,254	-3,741	-4,073	-4,742	-3,893	-3,846
							(-4,17)***	(-4,51)***	(-4,28)***	(-3,97)***	(-3,75)***	(-4,11)***
Excess_reserves$_{it}$ (percent)	-0,118	-0,129	-0,134	-0,125	-0,128	-0,133						
	(-5,06)***	(-5,47)***	(-4,77)***	(-5,19)***	(-5,72)***	(-4,83)***						
Observations	813150	813150	813150	813150	813150	813150	27105	27105	27105	27105	27105	27105
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower*Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Lender*Time FE	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (6), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (3) to (6) and (9) to (12) incorporate the effects of our idiosyncratic liquidity shock (deposits outflow) in accessing and pricing funds in the interbank market, respectively. All models have borrower, borrower*lender and time fixed effects to control for unobservable effects at the borrower, borrower-lender and time levels. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). Columns (6) and (12) include lender*time fixed effects. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

Table 4.5. The impact of the U.S. tapering in the interbank market

Variables	Panel A: Probability to access the market: P (zit =1)						Panel B: Pricing Models: Spread it					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
US tapering$_t$			0,052	0,047	0,043	0,052			3,021	3,945	4,317	3,724
			(3,51)***	(3,22)***	(3,45)***	(3,65)***			(4,21)***	(4,75)***	(4,23)***	(4,15)***
Size$_{it}$ [Log of assets (mln)]	0,091	0,108	0,103	0,108	0,175	0,168	-0,095	-0,087	-0,092	-0,077	-0,084	-0,073
	(3,24)***	(3,12)***	(2,98)***	(3,05)***	(3,14)***	(3,13)***	(-3,04)***	(-2,88)***	(-2,91)**	(-2,94)**	(-2,69)**	(-3,12)**
Capital ratio$_{it}$ (percent)	0,048	0,051	0,047	0,041	0,047	0,051	-0,065	-0,079	-0,071	-0,064	-0,071	-0,068
	(3,15)***	(3,18)***	(3,06)***	(2,84)***	(2,97)***	(3,14)***	(-2,65)**	(2,71)**	(3,14)***	(3,31)***	(3,21)***	(3,21)***
Npl$_{it}$ (percent)	-0,084	-0,087	-0,072	-0,075	-0,083	-0,075	0,058	0,061	0,047	0,053	0,047	0,043
	(-2,14)**	(-2,21)**	(-2,16)**	(-2,14)**	(-2,2)**	(-1,90)**	(2,27)**	(2,61)**	(2,77)**	(2,35)**	(2,38)**	(1,72)*
Liquidity_risk$_{it}$ (percent)		0,053	0,035	0,033	0,023	0,037		0,028	0,033	0,041	0,039	0,035
		(2,54)**	(2,17)**	(2,17)**	(2,12)**	(2,63)**		(3,06)***	(3,10)***	(3,28)***	(2,82)***	(2,34)***
Market Liq_risk$_t$ (percent)		-0,039	-0,047	-0,053	-0,045	-0,041		0,055	0,058	0,064	0,058	0,061
		(-2,13)**	(-2,74)**	(-2,86)***	(-3,32)***	(-2,24)**		(2,42)**	(2,85)**	(2,17)**	(2,31)**	(2,39)**
US tapering$_t$ * Size$_{it}$ [Log of assets (mln)]			0,012	0,013					-0,019	-0,013		
			(1,24)	(1,11)					(-1,91)*	(-1,82)*		
US tapering$_t$ * Capital ratio$_{it}$ (percent)			0,082	0,081					-0,015	-0,013		
			(3,30)***	(3,38)***					(-3,04)***	(-3,42)***		
US tapering$_t$ * Npl$_{it}$ (percent)			-0,012	-0,009	-0,011	-0,012			0,016	0,025	0,029	0,021
			(-1,04)	(-1,20)	(-1,33)	(-1,22)			(1,24)	(1,32)	(1,07)	(1,16)
US tapering$_t$ * Liquidity_risk$_{it}$ (percent)				-0,016	-0,014	-0,011				0,013	0,011	0,013
				(-3,12)***	(-2,83)**	(-3,34)***				(2,19)*	(2,05)*	(2,36)**
US tapering$_t$ * Market Liq_risk$_t$ (percent)				-0,012	-0,013	-0,009				0,024	0,017	0,014
				(-2,73)**	(-2,75)**	(-2,52)**				(3,17)***	(3,04)***	(3,41)***
Small$_{it}$ * npl$_{it}$ (percent)					-0,034	-0,025					0,017	0,012
					(-1,62)*	(-1,25)					(1,05)	(1,08)
Small$_{it}$ * Liquidity_risk$_{it}$ (percent)					-0,008	-0,007					0,011	0,013
					(3,55)***	(2,73)**					(3,46)***	(3,21)***
US tapering$_t$ * Small$_{it}$					-0,007	-0,005					0,139	0,134
					(-2,11)**	(-2,51)**					(2,08)**	(2,29)**
US tapering$_t$ * Small$_{it}$ * npl$_{it}$ (percent)					-0,011	-0,014					0,013	0,016
					(-1,38)	(-1,27)					(1,24)	(1,22)
US tapering$_t$ * Small$_{it}$ * Liquidity_risk$_{it}$ (percent)					-0,002	-0,001					0,019	0,017
					(-3,22)***	(-2,76)**					(2,31)**	(2,42)**
RL$_{ijt}$	0,041	0,041	0,044	0,049	0,038	0,042	-1,123	-1,054	-1,075	-0,876	-0,821	-0,723
	(7,20)***	(7,54)***	(8,10)***	(8,71)***	(8,11)***	(8,07)***	(-5,94)***	(-5,75)***	(-5,07)***	(-4,81)***	(-4,22)***	(-4,54)***
US tapering$_t$ * RL$_{ijt}$			0,014	0,009	0,017	0,013			-0,225	-0,198	-0,212	-0,248
			(1,05)	(0,90)	(0,85)	(1,11)			(-3,92)***	(-3,74)***	(-3,63)***	(-3,37)***
CB_Liq_supply$_t$ [ln (mln)]	0,014	0,011	0,017	0,016	0,011	0,014	-0,057	-0,061	-0,053	-0,067	-0,072	-0,063
	(1,48)	(1,50)	(0,98)	(1,08)	(1,12)	(1,06)	(-3,73)***	(-3,80)***	(-3,86)***	(-3,56)***	(-3,19)***	(-3,89)***
US tapering$_t$ * CB_Liq_supply$_t$ [ln (mln)]			0,009	0,011	0,008	0,01			-0,011	-0,015	-0,011	-0,015
			(2,15)**	(2,33)**	(2,27)**	(3,28)***			(-4,21)***	(-3,61)***	(-4,26)***	(-4,71)***
Inv_Mills ratio$_{it}$							-3,478	-3,657	-3,986	-3,341	-3,623	-3,734
							(-3,17)***	(-2,50)**	(-2,34)**	(-2,35)**	(-3,30)***	(-4,12)***
Excess_reserves$_{it}$ (percent)	-0,101	-0,112	-0,121	-0,124	-0,114	-0,117						
	(-4,91)***	(-4,82)***	(-4,29)***	(-4,83)***	(-4,19)***	(-4,37)***						
Observations	102060	102060	102060	102060	102060	102060	3402	3402	3402	3402	3402	3402
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Lender*Time FE	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (6), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (3) to (6) and (9) to (12) incorporate the effects of our aggregate liquidity shock (US tapering) in accessing and pricing funds in the interbank market, respectively. All models have borrower, borrower*lender and time fixed effects to control for unobservable effects at the borrower, borrower-lender and time levels. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). Columns (6) and (12) include lender*time fixed effects. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

Table 4.6. Idiosyncratic liquidity shocks: Bank's stability, secured funding and lending concentration

Variables	Panel A: Probability to access the market: P (zit =1)						Panel B: Pricing Models: Spread it					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Liquidity Shock$_{it-1}$			0,169	0,168	0,132	0,141			4,854	4,572	4,624	4,837
			(4,58)***	(4,25)***	(4,21)***	(3,95)***			(5,19)***	(5,12)***	(5,35)***	(5,12)***
Size$_{it}$ [Log of assets (mln)]	0,131	0,124	0,127	0,135	0,128	0,138	-0,146	-0,127	-0,108	-0,135	-0,127	-0,130
	(3,25)***	(3,78)***	(3,84)***	(3,28)***	(3,16)***	(3,22)***	(-3,62)***	(-3,47)***	(-3,09)**	(-3,28)**	(-3,39)***	(-3,45)***
z-score$_{it}$ (percent)	0,062	0,054	0,058	0,065	0,074	0,071	-0,032	-0,028	-0,019	-0,022	-0,017	-0,019
	(2,71)**	(2,45)**	(2,14)**	(2,61)**	(1,96)**	(1,89)*	(-2,25)**	(2,13)**	(2,26)**	(2,78)***	(3,19)***	(2,94)***
Npl$_{it}$ (percent)	-0,091	-0,086	-0,082	-0,071	-0,081	-0,075	0,047	0,055	0,062	0,058	0,052	0,047
	(-2,10)**	(-1,91)**	(-1,79)*	(-2,29)**	(-2,21)**	(-2,17)**	(2,18)**	(2,33)**	(2,08)**	(2,32)**	(2,28)**	(2,53)**
Liquidity_ratio$_{it}$ (percent)		0,049	0,069	0,075	0,072	0,062		-0,026	-0,031	-0,023	-0,025	-0,027
		(1,15)	(1,06)	(1,34)	(1,31)	(1,28)		(-2,17)**	(-2,29)**	(-2,40)**	(-1,82)*	(-2,24)**
Market Liq_risk$_t$ (percent)		-0,013	-0,017	-0,029	-0,023	-0,019		0,058	0,063	0,053	0,061	0,064
		(-2,05)**	(-1,96)**	(-2,27)**	(-1,83)*	(-1,93)**		(3,01)***	(3,24)***	(3,18)***	(2,52)**	(2,30)**
Liquidity Shock$_{it-1}$ * Size$_{it}$ [Log of assets (mln)]			0,013	0,011					-0,015	-0,012		
			(1,26)	(1,48)					(-1,73)*	(-1,82)*		
Liquidity Shock$_{it-1}$ * z-score$_{it}$ (percent)			0,011	0,026					-0,007	-0,011		
			(1,40)	(1,12)					(-2,04)**	(-2,21)**		
Liquidity Shock$_{it-1}$ * Npl$_{it}$ (percent)			-0,014	-0,017	-0,015	-0,013			0,008	0,006	0,007	0,003
			(-1,12)	(-1,29)	(-1,26)	(-1,24)			(1,84)*	(1,98)**	(2,11)**	(1,81)*
Liquidity Shock$_{it-1}$ * Liquidity_ratio$_{it}$ (percent)				0,015	0,011	0,009				-0,006	-0,005	-0,007
				(2,65)**	(2,45)**	(2,38)**				(-2,52)**	(-2,32)**	(-2,44)**
Liquidity Shock$_{it-1}$ * Market Liq_risk$_t$ (percent)				-0,008	-0,007	-0,004				0,014	0,013	0,011
				(-2,28)**	(-2,53)**	(-2,50)**				(2,12)*	(2,27)**	(1,94)**
BPI$_{ijt}$	0,035	0,035	0,031	0,041	0,038	0,028	-1,026	-1,058	-1,112	-1,082	-1,043	-0,973
	(4,96)***	(5,15)***	(5,74)***	(6,35)***	(5,16)***	(5,19)***	(-3,90)***	(-4,06)***	(-4,25)***	(-3,81)***	(-3,74)***	(-4,23)***
Liquidity Shock$_{it-1}$ * BPI$_{ijt}$			0,016	0,015	0,017	0,015			-0,206	-0,218	-0,236	-0,274
			(3,51)***	(3,37)***	(5,03)***	(4,26)***			(-3,25)***	(-3,25)***	(-2,97)***	(-3,15)***
Borrowing secured$_{it}$	0,012	0,018	0,013	0,023	0,019	0,022	-0,017	-0,011	-0,019	-0,024	-0,019	-0,015
	(1,21)	(1,07)	(1,78)*	(1,39)	(1,29)	(1,29)	(-1,25)	(-1,14)	(-0,96)	(-1,14)	(-1,34)	(-1,05)
Liquidity Shock$_{it-1}$ * Borrowing secured$_{it}$			0,004	0,008	0,004	0,005			-0,003	-0,004	-0,006	-0,007
			(1,75)*	(1,87)*	(1,42)	(1,28)			(-2,20)**	(-2,33)**	(-2,15)*	(-2,26)**
CB_Liq_supply$_t$ [ln (mln)]	0,015	0,011	0,019	0,014	0,011	0,013	-0,024	-0,031	-0,029	-0,032	-0,024	-0,028
	(1,30)	(1,14)	(1,22)	(1,22)	(1,33)	(1,16)	(-2,47)**	(-2,26)**	(-2,19)**	(-2,94)***	(-2,25)**	(-1,92)**
Liquidity Shock$_{it-1}$ * CB Liq_supply$_t$ [ln (mln)]			0,007	0,008	0,003	0,004			-0,011	-0,009	-0,011	-0,013
			(1,07)	(1,22)	(1,19)	(1,18)			(-1,15)	(-1,23)	(-1,03)	(-1,27)
Inv_Mills ratio$_{it}$							-6,135	-5,846	-5,024	-5,127	-4,573	-5,316
							(-3,75)***	(-3,97)***	(-4,02)***	(-4,48)***	(-4,28)***	(-4,02)***
Excess_reserves$_{it}$ (percent)	-0,205	-0,237	-0,216	-0,263	-0,249	-0,234						
	(-6,21)***	(-5,36)***	(-5,54)***	(-5,72)***	(-6,03)***	(-6,29)***						
Observations	813150	813150	813150	813150	813150	813150	27105	27105	27105	27105	27105	27105
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Lender*Time FE	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (6), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (3) to (6) and (9) to (12) incorporate the effects of our idiosyncratic liquidity shock (deposits outflow) in accessing and pricing funds in the interbank market, respectively. All models have borrower, borrower*lender and time fixed effects to control for unobservable effects at the borrower, borrower-lender and time levels. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). Columns (6) and (12) include lender*time fixed effects. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

Table 4.7. Aggregate liquidity shocks: bank's stability, secured funding and lending concentration

Variables	Panel A: Probability to access the market: P (zit =1)						Panel B: Pricing Models: Spread it					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
US tapering$_t$			0,063	0,058	0,042	0,051			3,104	3,373	3,296	2,652
			(3,28)***	(3,53)***	(3,63)***	(3,37)***			(5,14)***	(5,28)***	(5,72)***	(5,70)***
Size$_{it}$ [Log of assets (mln)]	0,086	0,097	0,101	0,119	0,122	0,117	-0,079	-0,086	-0,094	-0,075	-0,068	-0,075
	(3,45)***	(3,29)***	(3,08)***	(3,21)***	(3,15)***	(3,21)***	(-3,41)***	(-3,07)***	(-2,87)***	(-2,73)***	(-3,21)**	(-3,41)**
z-score$_{it}$ (percent)	0,051	0,043	0,040	0,053	0,059	0,046	-0,065	-0,079	-0,071	-0,072	-0,061	-0,051
	(2,26)**	(2,14)**	(2,18)**	(2,22)**	(2,13)**	(2,03)**	(-2,65)**	(2,71)**	(2,14)**	(2,35)**	(1,77)*	(2,23)**
Npl$_{it}$ (percent)	-0,077	-0,081	-0,075	-0,071	-0,079	-0,076	0,055	0,057	0,039	0,044	0,053	0,043
	(-2,26)**	(-2,18)**	(-2,34)**	(-2,27)**	(-2,19)**	(-1,87)*	(2,31)**	(2,41)**	(2,30)**	(2,56)***	(2,49)**	(2,21)**
Liquidity_ratio$_{it}$ (percent)		0,042	0,046	0,039	0,037	0,021		-0,018	-0,012	-0,014	-0,007	-0,018
		(1,26)	(1,18)	(1,30)	(1,18)	(1,19)		(-2,06)**	(-2,19)**	(-1,93)*	(-2,15)**	(-1,83)*
Market Liq_risk$_t$ (percent)		-0,032	-0,041	-0,051	-0,043	-0,053		0,046	0,051	0,055	0,059	0,068
		(-2,28)**	(-2,19)**	(-2,12)**	(-2,21)**	(-2,31)**		(3,28)***	(3,41)***	(3,25)***	(3,17)***	(3,54)***
US tapering$_t$ * Size$_{it}$ [Log of assets (mln)]			0,016	0,019					-0,015	-0,013		
			(1,04)	(1,18)					(-1,74)*	(-1,37)		
US tapering$_t$ * z-score$_{it}$ (percent)			0,017	0,009					-0,015	-0,018		
			(2,77)**	(2,36)**					(-2,04)**	(-2,31)**		
US tapering$_t$ * Npl$_{it}$ (percent)			-0,018	-0,015	-0,013	-0,011			0,019	0,021	0,018	0,022
			(-1,10)	(-1,19)	(-1,26)	(-0,99)			(2,30)**	(1,92)*	(2,29)**	-1,62
US tapering$_t$ * Liquidity_ratio$_{it}$ (percent)				-0,017	-0,021	-0,014				-0,012	-0,008	-0,013
				(-1,08)	(-1,32)	(-1,28)				(-2,47)***	(-2,33)**	(-2,19)**
US tapering$_t$ * Market Liq_risk$_t$ (percent)				-0,019	-0,013	-0,015				0,018	0,015	0,022
				(-3,25)***	(-3,21)***	(-3,38)***				(2,32)**	(3,11)***	(3,18)***
BPI$_{ijt}$	0,051	0,047	0,039	0,034	0,328	0,342	-1,021	-1,014	-1,072	-1,032	-1,003	-1,012
	(6,90)***	(7,33)***	(7,03)***	(6,27)***	(7,17)***	(6,27)***	(-3,72)***	(-4,18)***	(-4,20)***	(-3,43)***	(-3,35)***	(-3,82)***
US tapering$_t$ * BPI$_{ijt}$			0,011	0,014	0,015	0,013			-0,053	-0,061	-0,081	-0,054
			(1,86)*	(1,77)*	(2,28)**	(2,26)**			(-1,62)	(-1,25)	(-1,37)	(-1,35)
Borrowing secured$_{it}$	0,017	0,012	0,013	0,018	0,023	0,017	-0,013	-0,012	-0,018	-0,015	-0,012	-0,007
	(1,12)	(1,04)	(1,16)	(1,25)	(0,97)	(1,22)	(-0,95)	(-0,84)	(-0,77)	(-0,88)	(-1,08)	(-0,72)
US tapering$_t$ * Borrowing secured$_{it}$			0,004	0,008	0,003	0,008			-0,006	-0,008	-0,005	-0,004
			(1,98)**	(2,17)**	(2,35)**	(2,38)**			(-1,20)	(-1,26)	(-1,22)	(-0,82)
CB_Liq_supply$_t$ [ln (mln)]	0,011	0,018	0,012	0,011	0,015	0,019	-0,062	-0,057	-0,049	-0,061	-0,053	-0,055
	(1,23)	(1,08)	(0,91)	(1,21)	(1,25)	(1,02)	(-3,21)***	(-3,42)***	(-3,24)***	(-3,35)***	(-3,33)***	(-3,29)***
US tapering$_t$ * CB_Liq_supply$_t$ [ln (mln)]			0,009	0,007	0,007	0,008			-0,019	-0,022	-0,019	-0,017
			(2,15)**	(2,25)**	(2,18)**	(1,87)*			(-5,06)***	(-4,24)***	(-4,87)***	(-4,21)***
Inv_Mills ratio$_{it}$							-2,856	-3,162	-3,436	-2,834	-3,064	-2,922
							(-3,28)***	(-3,19)***	(-2,46)**	(-3,12)***	(-3,42)***	(-3,50)***
Excess_reserves$_{it}$ (percent)	-0,114	-0,109	-0,118	-0,122	-0,111	-0,115						
	(-4,02)***	(-4,23)***	(-3,74)***	(-3,92)***	(-3,74)***	(-3,82)***						
Observations	102060	102060	102060	102060	102060	102060	3402	3402	3402	3402	3402	3402
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Lender*Time FE	No	No	No	No	No	Yes	No	No	No	No	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (6), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (3) to (6) and (9) to (12) incorporate the effects of our aggregate liquidity shock (US tapering) in accessing and pricing funds in the interbank market, respectively. All models have borrower, borrower*lender and time fixed effects to control for unobservable effects at the borrower, borrower-lender and time levels. Time-variant lender controls are included in columns (4) to (6) and (10) to (12). Columns (6) and (12) include lender*time fixed effects. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

Table 4.8. Idiosyncratic liquidity shocks: lending reciprocity and bank heterogeneity

Variables	Panel A: Probability to access the market: P (zit =1)					Panel B: Pricing Models: Spread it				
	Baseline			Large Shocks		Baseline			Large Shocks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Liquidity Shock$_{it}$		0,142	0,134	0,072	0,063		4,626	4,122	3,876	3,542
		(4,71)***	(4,95)***	(5,37)***	(5,02)***		(4,19)***	(4,43)***	(4,89)***	(5,02)***
Size$_{it}$ [Log of assets (mln)]	0,132	0,138	0,126	0,084	0,076	-0,122	-0,128	-0,115	-0,352	-0,217
	(3,81)***	(3,17)***	(3,26)***	(4,23)***	(3,28)***	(-3,25)***	(-3,18)**	(-3,35)***	(-2,84)**	(-2,25)**
Capital ratio$_{it}$ (percent)	0,051	0,057	0,064	0,035	0,029	-0,031	-0,025	-0,019	-0,027	-0,032
	(2,37)**	(2,61)**	(2,03)*	(3,23)***	(3,12)***	(2,17)**	(2,42)***	(2,56)***	(3,11)***	(3,04)***
Liquidity_risk$_{it}$ (percent)	0,056	0,061	0,068	0,028	0,024	-0,021	-0,025	-0,029	-0,009	-0,011
	(1,09)	(1,12)	(1,03)	(1,04)	(1,18)	(-2,34)**	(-2,19)**	(-2,03)**	(-2,01)*	(-2,32)**
Market Liq_risk$_{t}$ (percent)	-0,017	-0,021	-0,023	-0,011	-0,005	0,047	0,049	0,038	0,063	0,075
	(-2,11)**	(-2,19)**	(-1,88)*	(-1,74)*	(-1,61)*	(3,11)***	(3,19)***	(2,63)**	(3,28)***	(2,25)**
LR_reciprocal$_{ijt}$	0,064	0,058	0,045	0,023	0,019	-0,812	-0,835	-0,843	-0,551	-0,487
	(3,57)***	(4,28)***	(4,01)***	(3,15)***	(3,24)***	(-4,08)***	(-3,51)***	(-3,73)***	(-4,84)***	(-4,24)***
Liquidity Shock$_{it}$ * LR_reciprocal$_{ijt}$		0,021	0,019	0,009	0,004		-0,321	-0,287	-0,173	-0,194
		(3,40)***	(3,91)***	(3,04)***	(2,72)**		(-3,18)***	(-2,79)**	(-3,28)***	(-3,17)***
Liquidity Shock$_{it}$ * Size$_{it}$ [Log of assets (mln)]		0,011	0,008	0,011	0,009		-0,014	-0,012	-0,015	-0,015
		(1,31)	(1,39)	(1,42)	(1,26)		(-1,94)*	(-2,01)*	(-1,98)*	(-1,98)*
Liquidity Shock$_{it}$ * Capital_ratio$_{it}$ (percent)		0,048	0,052	0,018	0,022		-0,005	-0,003	-0,011	-0,013
		(2,11)**	(2,16)**	(2,71)**	(2,56)**		(-1,17)	(-1,25)	(-2,78)**	(-3,03)***
Liquidity Shock$_{it}$ * Liquidity_risk$_{it}$ (percent)		0,011	0,006	-0,003	-0,001		0,005	0,003	0,007	0,011
		(2,58)**	(2,31)**	(-1,18)	(-1,12)		(2,13)**	(2,22)**	(3,14)***	(3,78)***
Liquidity Shock$_{it}$ * LR_reciprocal$_{ijt}$ *Size$_{it}$			0,007		0,004			-0,005		-0,004
			(2,02)*		(2,23)**			(-2,05)**		(-2,25)**
Liquidity Shock$_{it}$ * LR_reciprocal$_{ijt}$ *Capital_ratio$_{it}$			0,014		0,008			-0,004		-0,006
			(3,32)***		(2,47)**			(-2,51)**		(-3,21)***
Liquidity Shock$_{it}$ * LR_reciprocal$_{ijt}$ *Liquidity_risk$_{it}$			0,009		0,002			-0,007		-0,005
			(1,21)		(1,04)			(-1,03)		(-1,14)
CB_Liq_supply$_{t}$ [ln (mln)]	0,013	0,015	0,011	0,013	0,011	-0,024	-0,029	-0,021	-0,024	-0,028
	(1,23)	(1,17)	(1,27)	(1,12)	(1,37)	(-2,32)**	(-2,25)**	(-2,28)**	(-2,17)**	(-2,31)**
Liquidity Shock$_{it}$ * CB Liq_supply$_{t}$ [ln (mln)]		0,011	0,008	0,005	0,003		-0,005	-0,002	-0,005	-0,001
		(1,03)	(1,09)	(1,28)	(1,15)		(-1,19)	(-1,14)	(-1,25)	(-0,98)
Inv_Mills ratio$_{it}$						-5,657	-5,326	-4,745		
						(-3,71)***	(-3,62)***	(-3,58)***		
Excess_reserves$_{it}$ (percent)	-0,282	-0,234	-0,216	-0,129	-0,118				-4,723	-4,135
	(-5,12)***	(-5,61)***	(-5,72)***	(-5,36)***	(-5,24)***				(-4,82)***	(-4,30)***
Observations	813150	813150	813150	530315	530315	27105	27105	27105	17677	17677
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender*Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (6), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (7) to (12) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (1) to (3) and (6) to (8) are the probability and price models using the baseline definition of idiosyncratic liquidity shocks and the full sample, while columns (4) to (5) and (9) to (10) are the results of the probability and price models, respectively, but using the sample with only interbank loans affected by deposits outflow, and the indicator variable of liquidity shock comparing between large and small liquidity shocks. All models have borrower, borrower*lender, lender*time, and time fixed effects, in addition to time-variant lender controls. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

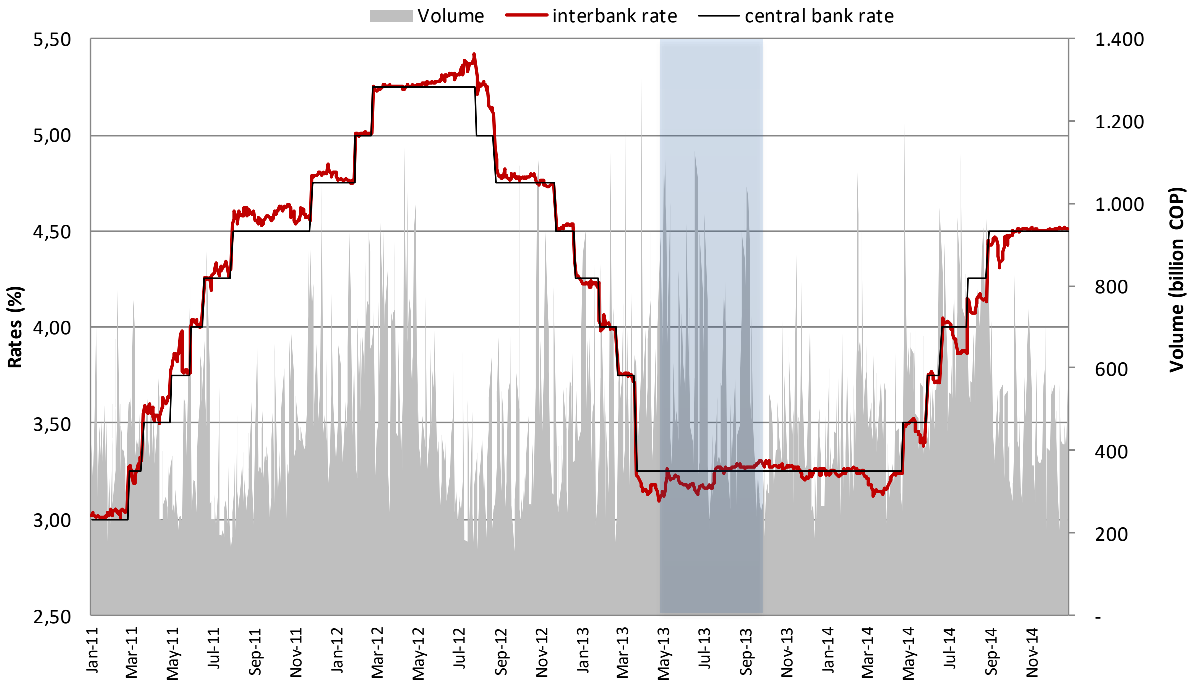
Table 4.9. Aggregate liquidity shocks: lending reciprocity and bank heterogeneity

Variables	Panel A: Probability to access the market: P (zit =1)							Panel B: Pricing Models: Spread it						
	Baseline			US Tapering Uncertainty		US Tapering High Prices		Baseline			US Tapering Uncertainty		US Tapering High Prices	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
US tapering$_t$		0,047	0,051	0,049	0,037	0,022	0,019		4,012	3,824	4,273	4,149	5,028	5,141
		(3,13)***	(3,22)***	(3,18)***	(3,25)***	(3,18)***	(3,23)***		(5,17)***	(5,20)***	(4,73)***	(4,81)***	(5,26)***	(5,37)***
Size$_{it}$ [Log of assets (mln)]	0,102	0,108	0,114	0,109	0,117	0,087	0,092	-0,081	-0,075	-0,072	-0,078	-0,067	-0,074	-0,055
	(3,12)***	(3,22)***	(3,04)***	(3,45)***	(3,28)***	(3,04)***	(3,11)***	(-3,14)***	(-2,97)**	(-2,84)**	(-2,73)**	(-3,26)***	(-2,71)**	(-2,82)**
Capital ratio$_{it}$ (percent)	0,045	0,051	0,057	0,062	0,058	0,063	0,067	-0,068	-0,063	-0,063	-0,078	-0,063	-0,055	-0,061
	(2,31)**	(2,23)**	(2,18)**	(2,31)**	(2,19)**	(2,35)**	(2,28)**	(2,17)**	(2,53)***	(2,30)**	(2,28)**	(2,35)**	(2,14)**	(2,28)**
Liquidity_risk$_{it}$ (percent)	0,036	0,029	0,031	0,023	0,021	0,019	0,024	0,023	0,017	0,021	0,024	0,031	0,033	0,029
	(1,45)	(1,39)	(1,27)	(1,42)	(1,25)	(1,26)	(1,14)	(2,13)**	(2,05)**	(2,11)**	(2,34)**	(2,19)**	(2,75)***	(2,28)**
Market Liq_risk$_t$ (percent)	-0,038	-0,032	-0,041	-0,039	-0,043	-0,055	-0,061	0,046	0,039	0,042	0,049	0,043	0,052	0,056
	(-2,26)**	(-1,94)*	(-2,03)**	(-2,16)**	(-2,12)**	(-2,24)**	(-2,31)**	(3,24)***	(3,45)***	(3,27)***	(3,30)***	(3,18)***	(3,64)***	(3,19)***
LR_reciprocal$_{ijt}$	0,058	0,049	0,056	0,052	0,042	0,036	0,039	-1,054	-1,026	-0,921	-0,935	-0,894	-0,902	-0,863
	(5,28)***	(5,67)***	(6,02)***	(5,72)***	(6,20)***	(6,40)***	(5,82)***	(-4,15)***	(-3,72)***	(-3,45)***	(-3,52)***	(-3,28)***	(-3,17)***	(-3,36)***
US tapering$_t$ * LR_reciprocal$_{ijt}$		0,012	0,015	0,013	0,014	0,012	0,015		-0,052	-0,059	-0,045	-0,051	-0,042	-0,039
		(2,11)*	(2,08)**	(2,26)**	(2,31)**	(2,23)**	(2,22)**		(2,11)*	(2,19)**	(2,28)**	(2,31)**	(2,21)**	(-2,19)**
US tapering$_t$ * Size$_{it}$ [Log of assets (mln)]		0,021	0,018	0,024	0,019	0,018	0,014		-0,014	-0,012	-0,018	-0,021	-0,017	-0,014
		(1,15)	(1,23)	(1,17)	(1,04)	(1,29)	(1,47)		(-2,02)*	(-1,95)*	(-1,53)	(-1,48)	(-1,55)	(-1,60)
US tapering$_t$ * Capital_ratio$_{it}$ (percent)		0,077	0,072	0,083	0,086	0,089	0,084		-0,017	-0,013	-0,018	-0,017	-0,022	-0,025
		(3,21)***	(2,97)***	(3,06)***	(3,27)**	(2,94)***	(2,88)***		(-2,94)***	(-3,23)***	(-3,32)***	(-3,11)***	(-3,46)***	(-3,38)***
US tapering$_t$ * Liquidity_risk$_{it}$ (percent)		-0,012	-0,011	-0,014	-0,013	-0,016	-0,011		-0,009	-0,011	-0,013	-0,018	-0,014	-0,012
		(-2,08)**	(-2,14)**	(-2,21)**	(-2,23)**	(-2,19)**	(-2,07)**		(2,09)*	(2,11)**	(2,25)**	(2,34)**	(2,27)**	(-2,18)**
US tapering$_t$ * LR_reciprocal$_{ijt}$ *Size $_{it}$			0.008		0.003		0.003			-0,006		-0,008		-0,005
			(2,95)***		(2,59)**		(2,34)**			(-1,43)		(-1,39)		(-1,44)
US tapering$_t$ * LR_reciprocal$_{ijt}$ *Capital_ratio$_{it}$			0,012		0,015		0,011			-0,007		-0,005		-0,009
			(2,28)**		(2,19)**		(2,89)***			(-2,94)***		(-2,72)**		(-3,03)***
US tapering$_t$ * LR_reciprocal$_{ijt}$ *Liquidity_risk$_{it}$			-0,012		-0,012		-0,012			-0,009		-0,007		-0,011
			(-1,02)		(-1,02)		(-1,02)			(-1,81)*		(-1,45)		(-1,28)
CB_Liq_supply$_t$ [ln (mln)]	0,011	0,012	0,019	0,014	0,013	0,016	0,019	-0,049	-0,052	-0,067	-0,045	-0,061	-0,069	-0,062
	(2,23)**	(2,34)**	(2,47)**	(2,75)***	(2,43)**	(2,98)***	(3,02)***	(-4,06)***	(-4,47)***	(-4,12)***	(-3,89)***	(-4,02)***	(-4,62)***	(-4,08)***
US tapering$_t$ * CB_Liq_supply$_t$ [ln (mln)]		0,007	0,009	0,006	0,005	0,008	0,011		-0,023	-0,032	-0,017	-0,023	-0,028	-0,032
		(2,22)**	(2,19)**	(2,31)**	(2,34)**	(2,45)**	(2,17)**		(-3,81)***	(-3,92)***	(-3,68)***	(-3,91)***	(-3,84)***	(-3,03)***
Inv_Mills ratio$_{it}$								-4,653	-5,726	-4,931	-4,752	-4,958	-5,025	-4,734
								(-3,29)***	(-3,18)***	(-3,34)***	(-3,07)***	(-3,29)***	(-3,61)***	(-3,46)***
Excess_reserves$_{it}$ (percent)	-0,118	-0,112	-0,123	-0,119	-0,109	-0,118	-0,114							
	(-4,35)***	(-4,26)***	(-4,71)***	(-4,36)***	(-4,02)***	(-4,08)***	(-3,92)***							
Observations	102060	102060	102060	73273	73273	123868	123868	3402	3402	3402	2443	2443	4129	4129
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-variant Lender controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender*Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents OLS parameter estimates of the Heckman two-stage procedure that corrects for sample selection bias. Panel A, columns (1) to (7), present the results of the selection models, where the dependent variable is the probability of a bank to borrow from the interbank market (z_{it} =1). Panel B, columns (8) to (14) correspond to the second stage estimates of the interest rate models in which the spread to the CB rate (in bps) is employed as a dependent variable (i.e. the price of liquidity (p_{it})). Columns (1) to (3) and (8) to (10) correspond to the baseline sample with the initial definition of the US tapering. In columns (4) to (5) and (11) to (12) the sample period is from March 26 to July 30, and the US Tapering variable is equal 1 during May 22 to July 30 (first stage of the tapering), and 0 during March 26 to May 21 (before the tapering). In columns (6) to (7) and (13) to (14) the sample period is from May 22 to December 18, and the US Tapering variable is equal 1 during July 31 to December 18 (second stage of the tapering), and 0 during May 22 to July 30 (first stage of the tapering). All models have borrower, borrower*lender, lender*time, and time fixed effects, in addition to time-variant lender controls. We cluster robust standard errors at the borrower bank level. Robust t-statistics in parentheses. *, **, and *** denote significance level at 1%, 5% and 10%, respectively.

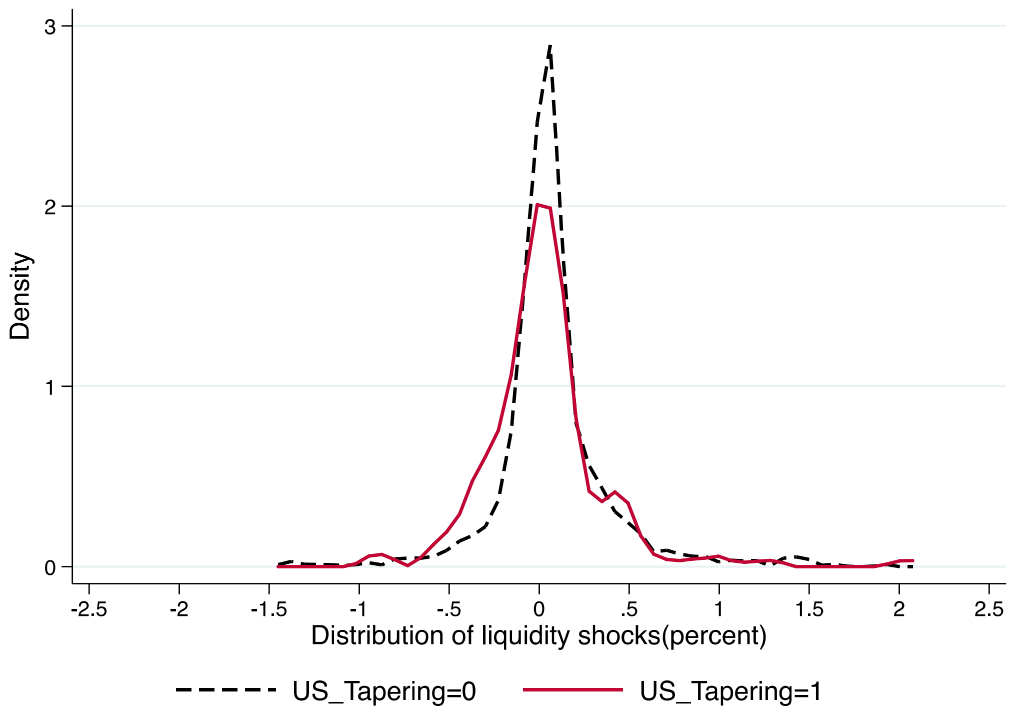
Appendix

Figure 4.1A. Interbank market rate, central bank rate, and daily volume of interbank funds



Notes: This figure depicts the overnight interbank market rate and central bank rate in percentage (%) during the period 2011-2014. Average daily amount traded in the interbank market in billions of COP (Right axis). Shared region corresponds to the U.S. tapering period: May-22-2013 to Sep-17-2013.

Figure 4.2A. Distribution of idiosyncratic liquidity shocks



Notes: This figure presents the distribution of the idiosyncratic liquidity shocks (i.e. deposits outflow) using daily data at the bank level. US_Tapering=0 corresponds to the full period from January 1, 2011 to December 30, 2014, without including the US Tapering period (May, 22 to December 30, 2013) i.e. when US_Tapering=1.

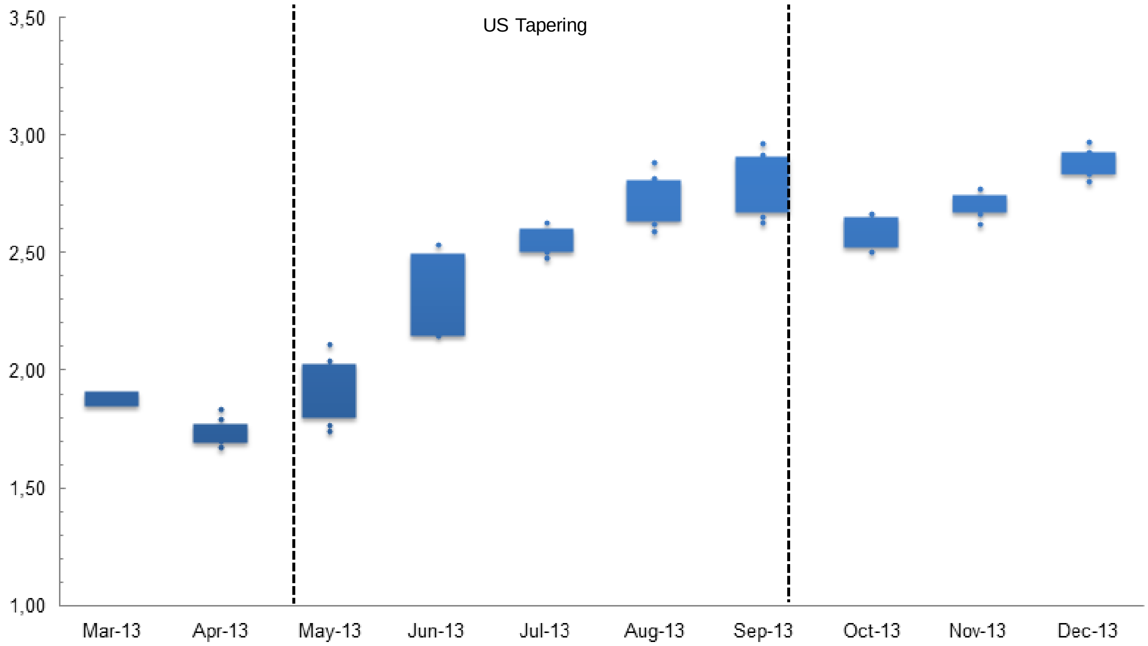
Table 4.1A. Correlation among lending relationship measures

	RL_{ijt}	BPI_{ijt}	$LR\_reciprocal_{jit}$
RL_{ijt}	1***		
BPI_{ijt}	0.42**	1***	0.22***
$LR\_reciprocal_{jit}$	0.35***	0.32**	1***

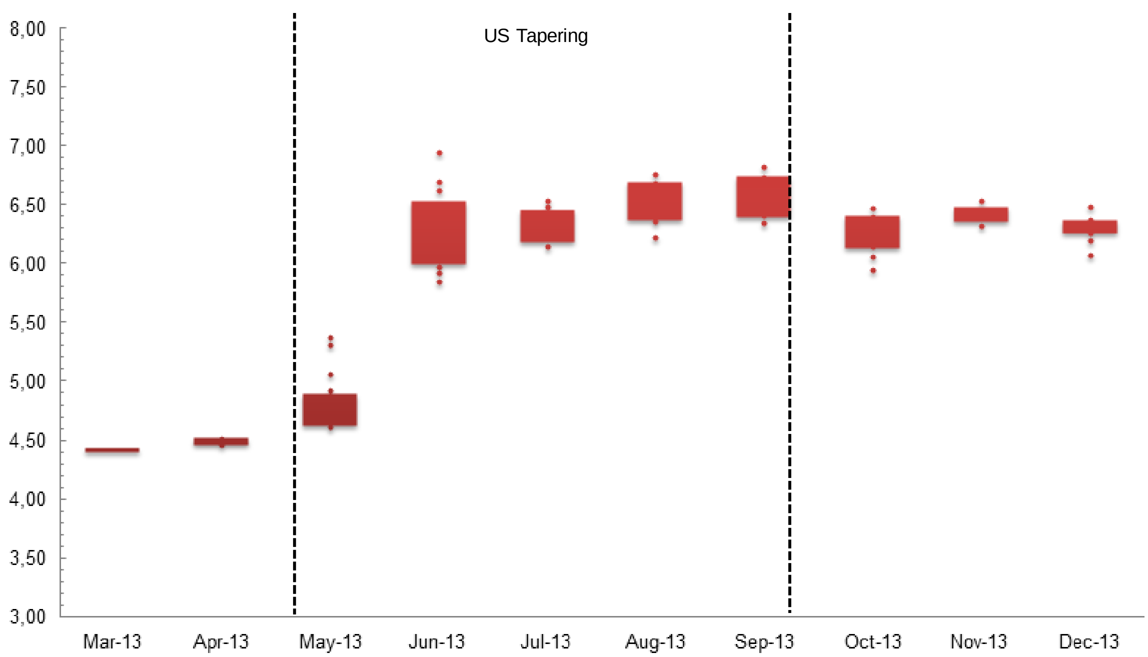
Notes: Definition of the lending relationship measures is provided in Table 2A. *** p>0.01, .**p>0.05.

Figure 4.3A. Government bills in U.S. and Colombia during the U.S. tapering

Panel (a) 10-years U.S. Treasury bills (yields, %)



Panel (b) 5-years Colombian bills (TES) (yields, %)



Notes: Panel (a) depicts the 10-years Treasury bills (yields, in %). Panel (b) shows the 5-years Colombian bills (TES) (yields, in %). Data is from the period March 26 and December 30, 2013. Dotted lines correspond to the U.S. tapering period: May 22 to September 17, 2013.

Table 4.2A. Summary statistics and definitions of the variables employed in the model

Variable	Definition	Mean	Std. Dev.	Min	Max	Obs.
p_{it} *(spread)*	The difference in basis points (bps) between the volume-weighted average interest rate (r_{it}) paid for a bank *i* of all its overnight unsecured loans during the day *t* and the central bank rate in *t* (r_{cbt}).	1,85	17,50	(148,32)	195,36	27105
$Loan_{ijt}$	Indicator variable equal 1 if the bank *i* borrows liquidity form bank *j* in the interbank market at time *t.*	0,73	0.27	0	1	813150
US tapering$_t$	Dummy variable equal to 1 during the period *t* in which the Fed announced to the market the possibility of reducing its purchase of assets: between May 22 and September 17, 2013, and 0 during the period immediately before (since the last change of the CB policy rate) i.e. March 23 and May 21, 2013. We also use two sub-periods composed by interbank loans observed during the period March 26 to July 30, 2013(US Tapering uncertainty), and during the period July 31 to December 18, 2013 (US Tapering high prices).	0.28	0,16	0	1	3402
$Liq.Shock_{it}$	Dummy variable equal 1 if the rate of change of the deposits of bank *i* is negative in *t-1* and, 0 otherwise. That is if a bank suffers a deposits outflow in t-1. We also use the variable *Large liquidity shock* that is equal to 1 if the deposits outflow in *t-1* for a borrower *i* is greater than the mean deposits outflow in t-1 and, 0 if it is below the mean deposits outflow in t-1.	0,43	0,75	0	1	27105
$Size_{it}$	Log of total assets (million COP, end of month)	14,68	1,92	9,08	18,42	1138
Capital ratio$_{it}$	Capital equity (Tier I and Tier II) over risk-weighted assets (end of month) (in %)	0,19	0,17	(2,93)	0,95	1138
Npl_{it}	Ratio of nonperforming loans (loans past due more than 90 days) over total loans (end of month) (in %)	0,04	0,02	0,00	0,20	1138

z-score$_{it}$	Sum of mean roa plus capital ratio in period t (car_t) over the standard deviation of roa (z-score= $\mu roa + car_t / \sigma roa$) computed on a rolling window of 12 months for the ROA and monthly for CAR. (in %)	4,51	4,82	(1,60)	7,55	1138
Excess_res$_{it}$	Reserve holding less the amount a bank needs to hold on a daily basis for the balance of the reserve maintenance period in order to exactly fulfil reserve requirements, divided by the average daily required reserves	17,06	39,21	(11,47)	293,24	27105
Liquidity_risk$_{it}$	Liquidity risk is measured as the standard deviation of daily change in reserve holdings during the last 30 days divided by reserve requirements	0,19	9,31	(82,57)	183,43	67950
Liquidity_ratio$_{it}$	Liquidity position computed as liquid assets over total assets (end of month) (%)	0,52	0,62	0,38	0,87	1138
Market_liq_risk$_{jt}$	Standard deviation of the normalized excess reserves among all banks j during the period t.	0,08	3,40	(14,87)	26,31	67950
RL$_{ijt}$	RL gauges the frequency of interactions between two banks in the interbank market and is computed by the logarithm of one plus the number of days a bank *i* has lent to bank *j* over a certain time of period *T* as: RL_{ijt}= log (1+ $\sum_{t \epsilon T}$ I(y_ijt>0)), with T = 30 days.	0,25	0,54	0,00	1,75	813150
BPI$_{it-1}$	Borrowing preference index (BPI) computed as the amount of funds borrowed by the bank *i* from a bank j at time t over a period *T* relative to the overall amount borrowed by bank *i* from all banks *j* over the same period *T* (with T = 30 days)	0,05	0,11	0,00	0,42	813150
LR_reciprocal$_{ijt}$	Lending reciprocity is defined as the Logarithm of (1 + the number of loans granted from borrower i to lender j during the last 30 days preceding day t)	(0,14)	(0,42)	(0,0)	(1,34)	813150
Borrowing secured$_{it}$	Dummy variable equal 1 if the bank i borrows funds in the secured money market in time t, and zero otherwise.	0,16	0,38	0,00	1,00	27105
CB_Liq_Supply$_t$	Log of the total liquidity supply of the central bank at time t (in billion COP)	29,36	0,48	27,81	30,35	1138

Borrowing Costs and the Role of Multilateral Development Banks: Evidence from Cross-border Syndicated Bank Lending

5. Borrowing Costs and the Role of Multilateral Development Banks: Evidence from Cross-border Syndicated Bank Lending

Abstract

Cross-border bank lending is a growing source of external finance in developing countries and could play a key role for infrastructure financing. This paper looks at the role of multilateral development banks (MDBs) on the terms of syndicated loan deals, focusing on loan pricing. The results show that MDBs' participation is associated with higher borrowing costs and longer maturities—signaling a greater willingness to finance high risk projects which may not be financed by the private sector—but it is also associated with lower spreads for riskier borrowers. Overall, our findings suggest that MDBs could crowd in private investment in developing countries through risk mitigation.

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5.1. Introduction

Long term financial flows to developing countries have been partly limited by high risk perception and the resulting high cost of borrowing (Collier and Mayer, 2014; Collier and Cust, 2015, Hayakawa, *et al*. 2013; WorldBank, 2015). An average developing country in sub-Saharan Africa, for instance, pays 300 basis points more than an average emerging market country in the bond market (Gueye and Sy, 2015).[1] Multilateral development banks (MDBs) can play two key roles in reducing such high-risk perception, and thereby, facilitating long term financial flows. First, MDBs can de-risk investment by signaling the profitability of projects allocating their own money in projects and loan syndicates, as well as taking a subordinate loan position and extending their *de facto* preferred creditor status (Rodrik, 1995; Hagen, 2009; Hainz and Kleimeier, 2012; Chelsky *et al*. 2013; Humphrey and Michaelowa, 2013; Humphrey, 2015; Pereira dos Santos and Kearney, 2018). Second, de-risking could be the result of MDBs' informational advantages and strong monitoring capacity—without which private lenders are reluctant to invest in projects that are deemed as too risky (Arezki *et al*. 2017)—. More generally, even though the largest share of lending to developing countries is provided by the private sector, international financial institutions—and especially MDBs—are a key player in development finance, especially in light of the 2030 Agenda for Sustainable Development and the financing needs for infrastructure investment (United Nations, 2015, International Monetary Fund, 2017)[2]

In this paper, we look at the de-risking role of MDBs using loan-level data on cross-border syndicated lending to emerging and developing countries during the period 1994-2015. Specifically, we address two interrelated questions. First, does the presence of an MDB in a loan syndicate affect loan terms, especially loan pricing? Second, does the involvement of an MDB mitigates borrower's riskiness, translating into lower loan spreads?

We focus on cross-border syndicated lending since it is an important—and growing—source of external finance in many emerging and developing countries (Nini, 2004; Godlewski and Weill,

[1] Similarly, Presbitero et al. (2016) show that, after controlling for several macroeconomic characteristics, sub-Saharan Africa countries are as likely as other developing economies to issue sovereign bonds, but they issue at a premium of more than 100 basis points.

[2] For an overview of the key functions of MDBs, see Griffith-Jones, 2016).

2008; Cortina et al. 2018). Syndicated loans account for about one third of total cross-border lending between 1995 and 2012, on average (Cerutti *et al.* 2015), and the size of the market is comparable to that of the bond market (World Bank, 2015). As countries develop, an increasing number of firms—for instance, large exporters and firms in the infrastructure and mining sectors in developing countries—access the cross-border syndicated loan market to support their expansion strategies. These loans are increasingly important as a source of finance for firms across the world. From a borrower's perspective, syndicated loans are generally less costly than bond issuance and a series of bilateral loan agreements; provide access to finance to borrowers that are unable to tap into the bond markets because of their low creditworthiness; and could also help to diversify the sources of external finance, promoting financial deepening and stability (Santos and Winton, 2008; Godlewski and Weill, 2008). From the lenders' standpoint, the syndicated loan market allows banks to generate fee income, diversify credit exposures to particular borrowers, industries, or countries as well as to make loans in markets where they lack origination capabilities (Sufi, 2007; Haselmann and Wachtel, 2011).

Although there is an emerging empirical literature on the pricing of syndicated loans, it is mostly limited to advanced and emerging economies and, to our knowledge, there is no study on the effect of MDBs' participation on loan pricing[3]. Most of the empirical literature analyzing the syndicated loans markets has been focused on advanced economies (see, for instance Dennis and Mollineaux, 2000; Carey and Nini, 2007; Sufi, 2007; Bosch and Steffen, 2011; Lim *et al*. 2014; Berg *et al*. 2016). Studies on cross-border lending to emerging markets have mainly investigated the drivers of loan syndication and the role of international banks (Eichengreen and Mody, 2000; Godlewski and Weill, 2008). However, little is known on cross-border syndicated lending to developing countries. One exception is the analysis by (Altunbaş and Gadanecz, 2004), who evaluate the determinants of loan pricing in syndicated loans granted to borrowers in developing countries between 1993 and 2001. They find that riskier borrowers pay higher prices albeit macroeconomic conditions in borrowers' countries play a predominant role in explaining loan pricing.

[3] Hainz and Kleimeier (2012) document that the participation of MDBs in the loan syndicate helps to mitigate political risk. Broccolini *et al.* (2018) focus on the mobilization effects of MDBs. However, there is no evidence on the role of MDBs in mitigating borrower riskiness.

Our analysis fills this gap by looking at how the syndicate structure—and in particular the presence of an MDB in the pool of lenders—affects loan terms. We use deal-level data on a large sample of about 17,000 syndicated loans granted to borrowers from 107 emerging and developing countries during the period 1994-2015. In addition to the loan-characteristics (price, amount, maturity, type of loan, etc.), the data includes loan-level information on lenders' name and location, number of banks in the syndicate, and type of bank (private bank or MDB), and borrowers' name, industry, location, and credit risk. We use a standard risk-return framework, as in Carey and Nini (2007) and Berg *et al*. (2016), to identify the drivers of syndicated loan terms and capture the role of MDBs. We also exploit loan-level information to test whether riskier borrowers pay a premium, and whether the participation of MDBs in the syndicate could mitigate the effect of borrower riskiness on loan pricing.

We have three main results. First, MDBs' participation is associated with higher borrowing costs and longer loan maturities. This finding indicates MDBs' higher capacity to lend at longer tenure than the private sector and—as long as spreads reflect borrower risk—the higher propensity of MDBs to finance risky projects—especially those in infrastructure—which may not be financed by the private sector. Second, the presence of an MDB in a syndicate is associated with a reduction of the effect of borrower riskiness on loan spreads by about one third, suggesting that MDBs' participation can lower borrowing costs for risky firms in developing countries. This effect could be the result of better information and monitoring of MDBs and the extension of their preferred creditor status. These results hold controlling for a large set of deal characteristics and absorbing time-varying unobserved heterogeneity at the industry and country level, as well as country*industry fixed effects. The results remain intact when considering different sub-samples and when using a matching technique, that compares loans with similar characteristics, but with and without an MDB in the loan syndicate. Third, our findings suggest that the role of MDB participation has more relevance during the downward phases of the economic cycle, which can alleviate the flight to home effects observed after 2008.

This chapter is organized as follows. Section 5.2 presents the data and the main stylized facts on the role of MDBs in the syndicated loan market. Section 5.3 discusses the analytical framework and the main results. Extensions and robustness tests are discussed in Section 5.4. Section 5.5 concludes.

5.2. Data and descriptive statistics

We collect data for more than 23,000 syndicated loans to emerging and developing countries originated during the 1994-2015 period from Dealogic Loan Analytics. A syndicate is formed by a pool of banks organized by a lead bank (arranger), who usually has a bank relationship with the borrower and has information on the borrower's creditworthiness. Then, to achieve the loan agreement, the arranger presents the loan conditions (e.g., amount, price, maturity, currency, type of loan) to the borrower and to the members of the syndicate. Each syndicate member has a separate claim on the borrower, albeit there is only a single loan agreement. Syndicated loans are priced at LIBOR plus a spread associated to borrower's credit risk. Participating banks charge several fees related to the type of loans (i.e., utilization, participation, facility, and underwriting fees). Thus, spread and fees capture different features of the lender-borrower relationship (Sufi, 2007b). We include only loans with full information on the size of the deal, the number and nationality of banks involved and some other basic deal characteristics. We restrict the sample to loan deals that involve borrower and lenders from different countries, to capture cross-border flows. Finally, in line with existing studies (e.g., Nini, 2004), we exclude loans to sovereigns, as they are likely driven by different factors compared to loans to non-sovereign entities (private sector and public sector firms). For each loan, the database offers detailed information on contractual characteristics: lender and borrower identity, location, industry, loan type (credit line vs. term loan), size, maturity, interest rate, and currency. After cleaning the raw data, we are left with 16,847 syndicated loans to 7,589 borrowers headquartered in 107 emerging and developing countries from 1994 to 2015. When looking at pricing, the sample is smaller because of data availability, as we have information on at most 7,571 deals (and 3,703 borrowers). **Table 5.A1** in the appendix presents the number of loan deals per country. The sample is dominated by the large emerging markets (China, Brazil, India, Mexico, Indonesia, and Turkey), but borrowers from low-income and lower middle-income countries represent more than 30 percent of the sample.[4]

Our baseline measure of loan pricing is the all-in interest rate spread, which includes the contract spread over LIBOR plus any annual fee and any upfront fee. This choice allows us to approximate the true economic value of the syndicated loan, as spread and fees capture different features of the lender-borrower relationship (Altunbaş and Gadanecz, 2004, Carey and Nini, 2007; Ivashina, 2009; Qian and Strahan, 2007; Berg *et al*. 2016). However, we also report results for spread and fees separately to test whether the MDBs' participation affect separate components of loan pricing differently. The average all-in interest rate spread is 351 bps, but there is a significant variability, with the interquantile range going from 180 to 475 bps. Loan maturity is measured in months: the median loan has a 3-year maturity, while 27 percent of loans have a maturity of one year or shorter, and only 10 percent of loans are longer than 10 years. Loan size is measured in 2011 constant USD and includes only the cross-country components of the deal, i.e., excluding the amount financed by banks headquartered in the same country as the borrower. The median loan is of about USD 65 million, with a quarter of deals being smaller than USD 21 million and another quarter larger than USD 170 million (**Table 5.1**).

5.2.1. MDBs' participation in syndicated loans: stylized facts

MDBs often participate in syndicated loans when the market could not provide funding because of high (perceived or actual) borrower's riskiness. MDBs' participation in a syndicated loan takes two forms: A/B loans and parallel loans. In the former, the MDB is the lender of record and holds a portion of the loan for its own account (the "A Loan"'), and invites external participants to cover the remaining portion (the "B Loan"). In case of a parallel loan, the MDB and the external source each conclude separate loan agreements with the borrower, on a project designed and administered by the MDB. With the A/B arrangement, MDBs can extend their preferred creditor status to the participants in the syndicate and the reduced risk and transaction costs could translate into lower spreads (Chelsky *et al*. 2013; Humphrey, 2015).[5] In

[4] Our results do not depend on one specific large country, nor on the presence of many countries with few loans, see Section 4.2.

[5] MDBs' loans—including A/B loans—are often excluded in debt restructuring even in crisis times. This is mainly because the IMF, the lender of last resort, has a non-tolerance policy on arrears to multilateral creditors (see IMF, 2013).

our sample, about 10 percent of the loan deals (1,694) have at least one MDB in the syndicate. On average, 63 percent of those loans have MDBs operating as lead arranger and the remaining of the loans have MDBs acting as another lender (participant) in the syndicate.[6] MDBs' participation is quite widespread across industries—with a concentration in agriculture and a lower presence in manufacturing and natural resources—and it is more common in lending to low and lower middle-income countries than in lending to borrowers located in emerging markets. In our sample, the European Bank for Reconstruction and Development and the International Finance Corporation (part of the World Bank group) together make 56 percent of the sample, with the European Investment Bank, the International Bank for Reconstruction and Development, the African Development Bank, the Inter-American Development Bank, and the Asian Development Bank being other key players.[7]

Table 5.2 compares syndicated loan characteristics with and without MDBs' participation. Loan deals with MDBs' participation are more expensive, have longer maturities and are smaller than those formed only by private banks. **Figure 5.1**, which plots the distribution of the all-in spread for loans with and without MDBs' participation, clearly shows that deals that involve MDBs have higher all-in spreads. On average, syndicated loans with MDBs' participation cost 96 bps more than loan syndicates formed solely by private institutions. This premium reflects an almost equal difference in the interest rate spread and in fees. The price difference is partly the reflection of significant differences in maturity, which is 32 months longer for loan deals that involve MDBs, and loan size, as deals with MDBs' participation are, on average, smaller by about USD 28 million. As these differences could reflect a number of differences in loan and borrower characteristics across the sample of deals, in the following analysis we look at these relationships in a multivariate setting and with a matching approach, to compare deals as similar as possible but that differ only in the presence of MDBs.

[6] This implies that (on average) in 37 percent of the loans in our sample the MDB asked a private lender to arrange the syndicate given its expertise in the market (i.e. investment banks) or it can be also the case that the MDB bought shares in those syndicates via the secondary syndicated loan market.

[7] Other MDBs' alternatives to provide finance include: i) co-financing with other international financial institutions; ii) guarantee facilities; iii) private placements of equity; and vii) debt co-financing with institutional investors, but they are not part of the cross-border syndicated loan market.

5.2.2. Macro Trends

The value of cross-border syndicated loans shows a cyclical trend with increasing flows in early 1990s followed by a fall in early 2000s (**Figure 5.2**).[8] Then, a rapid surge is observed until the onset of the global financial crisis, when inflows slightly declined, partly due to the "flight to home" effect (Giannetti and Laeven, 2012; Cerutti *et al.* 2015). MDBs' participation has also followed a similar pattern, assuming more importance, in relative terms, during the downward phases of the cycle—early 2000s and post-global financial crisis, consistent with a counter-cyclical role of MDB lending (Galindo and Panizza, 2018)—when loans with MDBs' participation amounted to up to 15 percent of all cross-border lending. In more recent years, however, this share declined to below 10 percent. The regional composition of these flows changed over time, with an increasing importance of cross border syndicated lending to low-income countries, especially in South Asia and Sub-Saharan Africa, starting from 2007 (**Figure 5.A2**, see also Gurara *et al.* (2018)). Lending to low-income countries has a strong component of infrastructure financing but it is still concentrated in a few recipient countries, even though, relative to the size of the economy, cross border syndicated bank lending has become as important in low-income countries as in emerging markets.

5.3. The empirical model

We look at the drivers of syndicated loan terms, focusing on the role of MDBs, in a model that controls for deal, lender, and borrower specific-characteristics (Carey and Nini, 2007; Berg *et al*. 2016). More precisely, we estimate the following equation:

$$Y_{jt} = \alpha MDB_{jt} + \gamma' \boldsymbol{X}_{jt} + \psi_{j(t)} + \theta_{j(t)} + \tau_t + \varepsilon_{\mathrm{it}} \qquad (1)$$

where the dependent variable is, alternatively, one of the pricing measures, size (in logarithm), or maturity (in months) of deal *j* originated in year *t*. The key explanatory variable measures the MDBs' participation in the syndicate with binary variable equal to one if at least one MDB is involved in the syndication of the loan, and zero if the syndicate includes only private banks[9].

[8] A very similar pattern emerges looking at the number of deals (see **Figure 5.A1**).

[9] We only know if the MDB is part of the pull of lenders and its role in the syndicate (i.e. lead arranger, bookrunner, facility agent, participant, etc.). Thus, we do not know whether the loan is an A/B loan or a parallel loan, as well as

The standard set of explanatory variables include: 1) the borrower's credit risk, measured by three categories—investment grade, leveraged, and highly leveraged; 2) the number of tranches of the loan; 3) the currency in which the loan is denominated, classified in three categories—USD, Euro, and other currencies; 4) a dummy equal to 1 if the loan is granted to public sector borrowers and 0 if the loan is to the private sector; 5) a dummy equal to 1 for term loans, and zero for credit facilities; and 6) a dummy equal to 1 if the loan has a guarantor, and 0 otherwise. Other than MDBs' participation, we look at the lender side of the deal measuring the concentration of the loan syndicate by the Herfindahl-Hirschman Index (HHI), calculated on bank shares in the loan. A more concentrated loan syndicate, as banks retain a higher share of the loan—especially lead arrangers—may signal lower risk and reduce moral hazard (Sufi, 2007; Bosch and Steffen, 2011).

Finally, the model is saturated with industry (ψ_j), country (θ_j), and year (τ_t) fixed effects to absorb unobserved heterogeneity across industries, countries and time, as loan terms could depend on global conditions as well as industry and country-specific unobservable factors. In the most demanding specification we absorb time-varying country and industry-specific unobserved factors that may drive loan terms by including country*year (θ_{jt}) and industry*year (θ_{jt}) fixed effects. Summary statistics and definition of all the variables are presented in **Table 5.1**.

5.3.1. Main Results

Table 5.3 shows the results of equation (1) when the dependent variable is the all-in spread. Column 1 to 5 incrementally add fixed effects up to our preferred specification with country*year and industry*year fixed effects. Finally, in column 6 we include country*industry fixed effects to allow for the possibility that industry-specific unobserved factors may affect loan pricing across countries differently (but not over time, which is absorbed by the year fixed

the identity of the loan guarantor, which are other forms of MDB participation (see **Section 5.2.1**.). In alternative specifications, we identify that the MDB participation as lead arranger is associated to significant higher loan prices, in line with our baseline results, albeit we do not observe significant effects on loan pricing for risky borrowers. This may suggest that what matters most is the presence of the MDBs in the pull of lenders regardless from their role in the syndicate. In **Table 5.7**, we observe that loans with guarantors have longer maturities but—because of we do not know the guarantor's identity—we are unable to check the specific effect of MDBs as guarantors on loan terms. Using information about the type of loan (credit facility vs. term loan), we find a significant effect of the de-risking role of MDB participation; especially for term loans (see **Section 5.4.2**. and **Table 5.11**).

effects). The comparison of the R^2 across specifications indicates that global shocks, captured by year fixed effects, play a key role in explaining the variation in loan prices (the R^2 increases from 0.38 to 0.51 between column 1 and 2), while the role of country-specific factors is smaller (columns 2 versus 3). The inclusion of time-varying country and industry fixed effects raises the R^2 to 0.66 (column 5), suggesting that our model is able to capture two third of the observed variation in loan prices across borrowers.

Regardless of the model specification, the coefficient of the MDBs' participation dummy is always positive and statistically significant, raging from 82 (column 2, with country and year fixed effects) to 45 (in the most demanding specification of column 5 with country*year and industry*year fixed effects). Taking the latter as our preferred and conservative specification, our results imply that the price of loans with MDBs' participation is higher by 45 bps or 13 percent (relative to the average all-in spread of 351 bps). If spreads reflect borrower risk (Strahan, 1999), this result would suggest that MDBs self-select into loans with higher risk—and therefore higher spreads—that could not otherwise be financed by the private sector, in line with the evidence discussed by Hainz and Kleimeier (2012) on a large sample of syndicated loans.

The set of coefficients on deal characteristics are broadly in line with existing evidence. We find that smaller loans and those with longer maturity are associated with higher prices (Carey and Nini, 2007; Ivashina, 2009; Berg *et al*. 2016). In particular, taking the results of column 5, an additional year of maturity is associated with a 9 bps increase in the all-in spread, reflecting the increasing risk premium for loans with longer maturities. A higher number of tranches in the deal is also associated with higher prices, consistent with an adverse effect of loan complexity on pricing (Lee and Mullienaux, 2004; Maskara, 2010; Lim *et al*. 2014). Borrower's credit risk has an important effect on loan pricing. Highly leveraged and leveraged borrowers pay significantly more than investment grade borrowers. The estimated premium is sizable and robust across all specifications. A highly leveraged borrower pays on average 365 bps more than an investment grade borrower while leveraged borrowers pay a premium of 115 bps (column 5). This result supports the presence of market discipline in the syndicated loan market and is consistent with the model developed by Diamond (1991), and with existing evidence from the syndicated loan market in advanced economies (Santos and Winton, 2008; Haselmann and Wachtel, 2011; Lim *et al*. 2014}.

Loans in Euro and in other currencies have a discount compared with loans in USD, in line with previous evidence from syndicated loans in emerging markets (Eichengreen and Mody, 2000). Interestingly, term loans are relatively more expensive than credit lines. On average a term loan costs 37 bps more than a credit facility (column 5), consistent with the view that firms with access to credit lines are generally more likely to have high cash flows and are less financially constrained (Sufi, 2007b; Acharya *et al*. 2014}. Moreover, borrowers from public sector companies and government pay lower prices (55 bps less) than private sector ones, suggesting the importance of (implicit) sovereign guarantees on loan pricing. Deals with a guarantor do not show any statistical difference in price from loans without guarantor. In line with existing evidence (Qian and Strahan, 2007), syndicated loans with higher concentration of lenders (as measured by the HHI) are associated with lower prices: on average, one standard deviation in the HHI is associated with a discount of 26 bps (column 5). This result is robust across all specifications and suggest that a higher concentration of banks' shares in the syndicate may signal a greater willingness to lend, which can be associated with a lower default risk (Sufi, 2007; Bosch and Steffen, 2011).

Results hold when we use spread and fees separately as alternative measures of loan pricing (see **Table 5.4**). In particular, the premium due to the presence of MDBs in the syndicate is almost equally split between higher fees (19 bps) and higher loan spreads (25 bps). All the other variables have relatively similar effect on the two components of the price structure, with the exception of maturity, term loans and the degree of syndicate concentration, which have larger effects on fees than on spreads.

5.3.2. The effect of borrower riskiness on loan spreads

MDBs often participate in syndicated loans when the market could not provide funding because of high (perceived or actual) borrower's riskiness. Simply comparing investment grade and risky loans (e.g., leveraged and highly leveraged loans) does not show any propensity of MDBs to join risky loan deals.[10] However, to the extent that the all-in spread reflects credit risk (Strahan, 1999), **Figure 5.1** and the baseline regressions (see **Table 5.3**) suggest that there is a positive correlation between (unobserved) risk and MDBs' participation. On the other hand,

[10] The share of loan deals with MDBs' participation which are classified as leveraged or highly leveraged is 22%; this share is 25% for deals without any MDB in the syndicate.

MDBs are also expected to reduce the cost of borrowing through their de-risking measures, including informational advantages, better monitoring, and the extension of their *de facto* senior creditor status. Information on the broader investment environment and the quality of government policy-making is a public good that may not be supplied by private agents.[11] MDBs are better positioned to internalize the costs of such information provisioning (Rodrik, 1995). Through their global and regional membership as well as collective agreements, MDBs have access to government data that enable them to monitor government policies in several countries. In addition, MDBs have the right incentive to collect (and disseminate) quality information as they commit their own resources. Finally, MDBs' participation by itself serves as a guarantee given that loans with the involvement of MDBs are often excluded in debt restructuring even in crisis times and serviced regularly.

To test whether MDBs' participation can mitigate the effect of borrower riskiness on loan spreads, we perform two exercises by interacting the MDBs participation dummy with two variables that could proxy for borrower creditworthiness. First, we identify risky loan deals with a dummy equal to one for those classified as leveraged or highly leveraged (*Risky*). Second, we proxy borrower riskiness using the country credit risk rating—an indicator of sovereign creditworthiness provided by Institutional Investor country credit rating dataset.[12] In particular, we define a dummy variable *High country risk* to identify borrowers which are located in countries in the bottom half of the distribution of the country credit risk rating variable.

A simple inspection of the data seems to support the hypothesis that MDBs could mitigate the effect of riskiness on borrowing costs (**Figure 3**). While there is a strong association between borrower riskiness and the all-in spread for deals that do not have any MDB involved (panel a), the presence of an MDB in the syndicate allows risky (leveraged and highly leveraged) borrowers to obtain loans priced similar to those obtained by less risky (investment grade)

[11] Hainz and Kleimeier (2012) argue that MDBs provide a so-called "political umbrella" because these banks can use their leverage to influence governmental decisions and deter adverse events that would negatively affect the project outcome.

[12] The dataset is published by Euromoney Institutional Investor PLC, and contains ratings of sovereign creditworthiness for 184 countries, from September 1979 to September 2016. Ratings are based on an assessment on country's fiscal sustainability, debt and liquidity, economic structure and performance, monetary policy and financial stability, balance of payments and political environment. The ratings grade each country on a scale from 0 to 100, with a rating of 100 given to those countries with the lowest chance of defaulting on their government debt obligations.

borrowers (panel b). To test this hypothesis more formally, **Table 5.5** presents the results of the pricing model using our specifications with country*year and industry*year fixed effects, looking separately at the all-in spread, as well at spread and fees. For each price measure, in the first column we include the interactions between the MDB participation dummy and the borrower riskiness indicator (*Risky*), while in the second column we replace the deal-specific riskiness measure with the dummy for the sovereign riskiness (*High country risk*).

The coefficient on the interaction term MDB*Risky is -60, indicating that the effect of borrower riskiness (157 bps) is reduced by 60 bps, corresponding to a drop of about 38 percent (column 1). This result remains significant even when considering spread and fees separately, although it is larger and more precisely estimated for the former (columns 3 and 5). Consistent with these finding, and in line with existing evidence that parties could invite MDBs to participate in the loan syndicate to compensate for the high country risk level (Hainz and Kleimeier, 2012), we find that the presence of an MDB in the syndicate is associated with significantly lower borrowing costs (41 bps, corresponding to about 27 percent) for companies headquartered in riskier countries, even controlling for deal characteristics, including the borrower's creditworthiness.

5.3.3. Infrastructure and public sector lending

In this section we look at two other dimensions that could matter for the way in which MDBs participation in syndicated loans can affect pricing. First, given the increasing and prominent role of MDBs in infrastructure financing (Humphrey, 2018), we are interested in the implications of MDBs' participation on borrowing costs for infrastructure projects. On the one hand, one could expect a lower cost due to risk mitigation measures, as MDBs bring close supervision and credit enhancement instruments. However, it could also be the case that MDBs self-select into loans for long-term projects with high risks, that might not match the risk profile of private sector investors. We discriminate between these two hypotheses interacting the MDB participation dummy with the infrastructure project loans indicator. The coefficient of the interaction term is positive and significant, meaning that infrastructure loans with MDBs' participation are about 66 bps more expensive than similar loans financed entirely by commercial banks (**Table 5.6**, column 1). This result, which is mostly driven by the change in spread rather than in fees (columns 3 and 5), would suggest that MDBs play a key role in infrastructure financing, as they tend to finance infrastructure projects with higher risks compared to similar projects financed by commercial banks alone.

As a second exercise, we allow MDBs' participation to have a different effect on loan prices for private and public sector borrowers. We observe that MDBs' participation is associated with significantly lower borrowing costs for public sector firms, suggesting a key role of MDBs for public sector financing. This effect is economically sizable, as the presence of an MDB in the syndicate almost double the reduction in the all-in spread of public sector borrowers compared to private sector ones (**Table 5.6**, column 2). This effect is almost equally large across spread and fees, albeit in the latter case the point estimate is not statistically significant (column 6).

5.3.4. Other loan terms

Having focused on how MDBs' participation is associated with loan pricing, we now test in the same multivariate framework whether loan deals with MDBs' involvement are smaller in size and longer in maturity than other comparable loans, as suggested by the descriptive analysis (see **Table 5.2**). Results are presented in **Table 5.7**, in which the dependent variable is, alternatively, loan size (in million of USD) in columns 1-3 and loan maturity (in months) in columns 4-6. For each loan term, we report the main specifications with country, industry and year fixed effect, time-varying industry and country fixed effects, and country*industry and year fixed effects.[13]

The presence of MDBs is associated with lower loan size compared to loans from syndicates formed only by private banks (column 1). According to the estimates in column 2, the difference in loan size is economically meaningful, as deals with MDBs are on average USD 70 million smaller than loans granted only by commercial banks—almost 40 percent smaller than the average loan, which amounts to about USD 180 million. This result would suggest some caution when discussing the scope of MDBs in directly mobilizing private sector resources, especially

[13] Results are based on the large sample of almost 15,000 loan deals, but they remain qualitatively the same when restricting the sample to deals for which the information on the all-in spread is non missing; see **Table 5.A4**.

in light of the large financing needs for achieving the Sustainable Development Goals outlined in the 2030 Agenda for Sustainable Development.[14]

Moving to other deal characteristics, we find that highly leveraged borrowers obtain smaller loans, confirming the importance of market discipline. Longer and more complex loans are associated with larger loan size, while term loans are generally smaller than credit facilities by around USD 35 million. Finally, deals with a higher degree of lender concentration are also smaller, suggesting that risk diversification—as more lenders enter into the syndicate—contributes to increase lending in the syndicated loan market (Dennis and Mollineaux, 2000; Sufi, 2007).

MDBs' participation is associated with loans with longer maturities compared to loan syndicates exclusively composed of private banks. The difference is economically meaningful, ranging from about 25 months to 27 months (columns 4-6). Taking the specification of column 5 with time varying fixed effects as a baseline, we observe that loans with an MDB in the syndicate are, on average, 27 months longer than those in which only private banks are involved. This result is consistent with evidence showing that MDBs have a greater capacity to lend at longer tenure than the private sector, and mostly provide longer maturities than the private sector (Chelsky *et al*. 2013; Ehlers, 2014; Inderst and Stewart, 2014).

The coefficients of the other deal characteristics are consistent with the existing evidence. Loans with more tranches, larger amount, denominated in currencies other than the dollar, and term loans are associated with longer maturities. As expected, loans to leveraged and highly leveraged borrowers have lower maturities compared to loans to investment grade borrowers, which confirm our previous findings on market discipline (i.e. safer borrowers borrow at lower prices and longer maturities compared to riskier borrowers). Deals with a guarantor also have longer maturities than those without a guarantor, confirming that the presence of guarantees benefit loan terms. Syndicate concentration is associated with significantly longer loan

[14] However, MDBs can also catalyze private investment on a broader scale through advice, support for policy reform, capacity building, and demonstration effects. See Broccolini *et al.* (2018) for evidence of the catalytic effects of MDBs in the syndicated loans market. A recent joint report by MDBs confirm that the most of the total mobilization effect by MDBs is indirect, while direct mobilization account for about 30 percent of all private sector resources mobilized in 2016 (World Bank, 2017).

maturities, suggesting that banks tend to keep larger shares in loans with longer maturities. This result, in conjunction with our findings in the price specification, may indicate that concentrated syndicates seem to lend at better terms (Qian and Strahan, 2007).

5.4. Extensions and robustness

5.4.1. Matching

Our main analysis is conducted in a standard multivariate setting, in which we control for a large set of observable loan characteristics and time, industry and countries fixed effects, to isolate the effect of MDBs' participation on loan terms. However, unobserved heterogeneity could bias our results, if it is correlated with the participation of MDBs in the syndicate. In an ideal setting, we would like to observe two identical loan deals; with the only exception that one involves an MDB in the pool of lenders and the other not. One way to get closer to this setting is to match *treated* (e.g., those with MDBs' participation) and *untreated* (i.e., those without MDBs' participation) along many observable dimensions to estimate the average treatment effect (ATE). In particular, we use the nearest-neighbor matching estimator and we do: i) exact matching on loan type (i.e., we compare within credit facilities and term loans), and ii) nearest-neighbor matching using the set of covariates used in the baseline model, including year, industry and country fixed effects.

The results—shown in **Table 5.8**—are consistent with what we found in the multivariate setting. Comparing the sample difference in the average all-in spread across loans with and without MDBs' participation with the ATE estimated after the matching indicates that most of the effect of MDBs' participation seen in the univariate setting is accounted for by observable deal characteristics. However, even after the matching, the ATE indicates that loan deals with MDBs' participation are, on average, priced at a higher all-in spread (33 bps), a result very close to our baseline (**Table 5.3**, column 5). This difference is driven exclusively by a higher spread, while fees are not statistically different across loan deals with and without MDBs (columns 2 and 3). We also confirm that the involvement of an MDB in the syndicate is associated with longer loan maturities, and lower loan volume (columns 4 and 5).

Finally, in **Table 5.9** we perform a slightly different exercise to look at the interaction between MDB´s participation and borrower riskiness. In this case, we consider the dummy for leveraged and high leveraged borrowers (*Risky*) as the treatment and we split the sample between loan deals with and without MDBs' participation to test whether the effect of borrower risk is indeed lower in the former than in the latter. The result supports our hypothesis, as risky loans pay a premium of 204 bps on the all-in spread when the syndicate is composed of only commercial banks, while this premium decreases to 130 bps when MDBs participate in the loan syndicate. This effect—74 bps—corresponds to a 36 percent reduction, a value very close to what estimated in the baseline (Table 3, column 1).

5.4.2. MDBs' participation before and after the GFC

In **Figure A1** and **Figure A2** we observe a decline in both number of deals and amount of loans during 2008 and 2009, which is associated to the global financial crisis, when inflows declined, partly due to the flight to home effect. We document that MDBs' participation has followed a counter-cyclical pattern, assuming more importance, in relative terms, during the downward phases of the cycle—early 2000s and post-global financial crisis—when loans with MDBs' participation amounted to up to 15 percent of all cross-border lending, consistent with a counter-cyclical role of MDB lending in financial markets (Galindo and Panizza, 2018). To shed light on this regard, we split the sample in two periods: pre-crisis (1994-2007) and post-crisis (2008-2015), and then estimate our baseline models of loan pricing, loan pricing and MDB participation, and loan terms and MDB participation.

Table 5.A5 presents the results of the pricing model using the most demanding specification with year fixed effects and country*year fixed effects. We observe that the estimated effect of MDB participation on loan pricing remains in similar levels than the baseline in both the pre-crisis and post-crisis periods. Note that the estimated effects of the deal characteristics hold and keep similar significance levels than in the baseline model. In **Table 5.A6.1** and **Table 5.A6.2**, we confirm that the involvement of an MDB in the syndicate is associated to lower borrowing costs for risky borrowers during the pre-crisis and post-crisis periods, respectively. When we look at the other loan terms, we observe that the effect of MDB participation on deal size is negative and statistically significant in the pre-crisis period (as observed in the baseline), but it is no longer significant in the post-crisis period (**Table 5.A7.1** and **Table 5.A7.2**). This result

indicates that after 2008 the size of the loans is not statistically different for syndicates formed only by private banks compared to those with MDB participation. Moreover, the effect of MDB participation on loan maturity is almost twice in the post-crisis period compared to the pre-crisis period. These findings can be related to the increase in the supply of loans with MDB participation in the post-crisis period, which reached 15% of the total cross-border lending (**Figure 5.A2**), as a result of the flight to home effect observed during 2008-10 period (Giannetti and Laeven, 2012; Cerutti et al. 2015).

In **Table 5.A6.1** and **Table 5.A6.2** we observe that the MDB participation in the syndicate is associated to lower borrowing costs for risky borrowers during the pre-crisis and post-crisis periods. This result is in line with our findings in the baseline model (**Table 5.5**) and in the matching exercise (**Table 5.9**), implying that MDBs may have a higher propensity to participate in syndicated loans for risky borrowers, which can translate in lower borrowing costs for those firms. To test this prediction, we employ a probit model that allows to estimate the likelihood of a high-risk loan being originated by a syndicate with MDB participation. We define as dependent variable the *Risky* indicator, which is equal to 1 if the borrower has a credit rating of leveraged and highly leveraged, and 0 if it has investment grade rating, and then focus on the effect of the MDB participation on the probability of lending to a risky borrower. We control for the deal-characteristics of our baseline model and include year, and country*industry fixed effects. The model is estimated by maximum likelihood using the baseline sample, as well as for the pre-crisis and post-crisis periods.

The results are presented in **Table 5.A8**. The estimated coefficient of the MDB variable indicates that, for the baseline period, the probability that a risky loan will be granted for a syndicate including an MDB is 19% larger compared to a syndicate formed only by private banks. Interestingly, this probability is 16% during the pre-crisis period, and increases to 23% in the post-crisis period. These results suggest that MDBs tend to select loans for risky borrowers, confirming our hypothesis that supports the findings in **Table 5.3** and **Table 5.9**. Moreover, the fact that MDB participation has a higher effect during the post-crisis period adds evidence on the potential counter-cyclical role of MDB lending, as risky borrowers becomes more credit rationed during the downward phases of the cycle (Ivashina and Scharfstein, 2010).

5.4.3. Robustness

We test the robustness of our main findings running a set of additional tests. First, we consider the fact that our sample is characterized by two features: the concentration of many deals in few countries (especially China, India and Mexico) and the presence of many countries (74) with a small number of loan deals. In Table 10 we replicate our main results—the standard association between MDBs' participation and the all-in spread and the de-risking effect—dropping the borrowers headquartered in China (columns 1-2); in China, India and Mexico (columns 3-4); and in the 74 countries which have less than 50 deals in our sample over the whole period 1994-2015 (columns 5-6). In all the three cases, the main findings on the role of MDBs on loan pricing both for an average and a risky borrower remain intact.

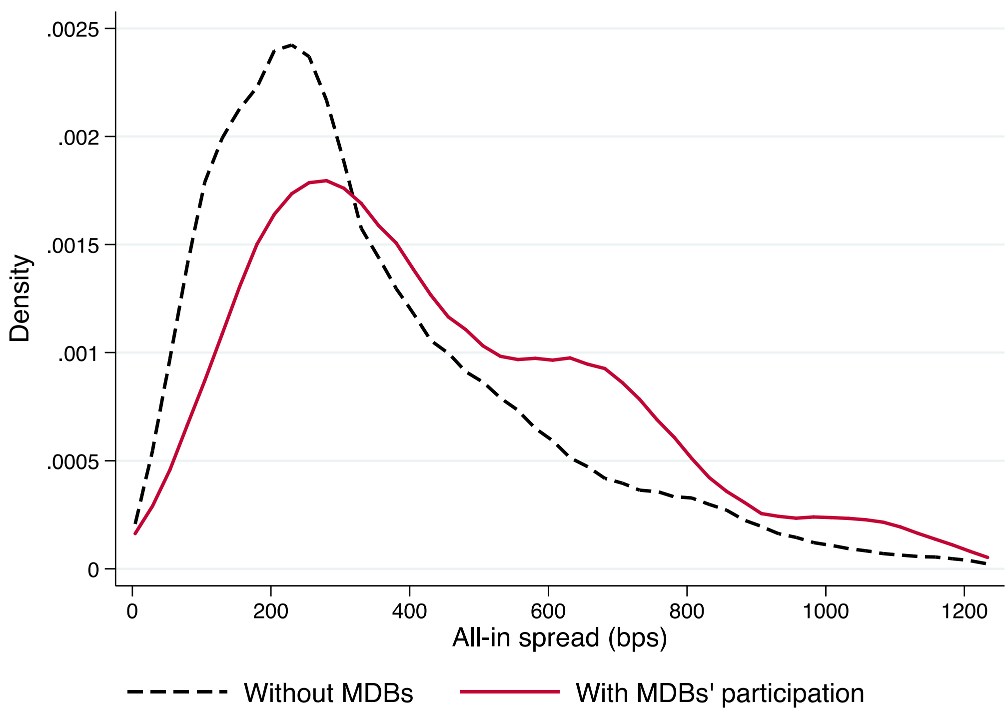
Second, we run a separate analysis for credit lines and term loans, on the ground that their pricing structure is likely to differ for several reasons, related to the different options included in the contracts (e.g., to draw on a line of credit, or terminate a loan contract) (Berg *et al*. 2016) and to the role of liquidity risk for participating banks (Gatev and Strahan, 2009). We find differences in how some loan characteristics, such as the syndicate concentration and maturity, affect all-in spread across credit lines and term loans (**Table 5.11**). MDBs are more often involved in term loans—63% of deals with MDBs' participation are term loans—. In this case, consistent with the hypothesis of risk mitigation through better information and the extension of the preferred creditor status, the involvement by an MDB in the syndicate significantly lowers borrowing costs for risky borrowers. On average, MDBs are not associated with higher borrowing costs, and the standard positive association between MDBs' participation and spreads is in place only for non-risky borrowers (columns 4-6). By contrast, the reduction of borrowing costs for risky borrowers when MDBs are involved in the loan deal is smaller and less robust when considering credit facilities, for which the risk mitigation via preferred credit status is not in place.

Finally, we cluster standard errors at the country level, rather than at the country-year level, as done throughout the paper. All our findings on the role of MDBs remain statistically significant. The replication of **Table 5.3** with the alternative clustering shows that the change of the standard errors is relatively limited and, in some cases, our baseline estimates are more conservative (**Table 5.A3**).

5.5. Conclusions

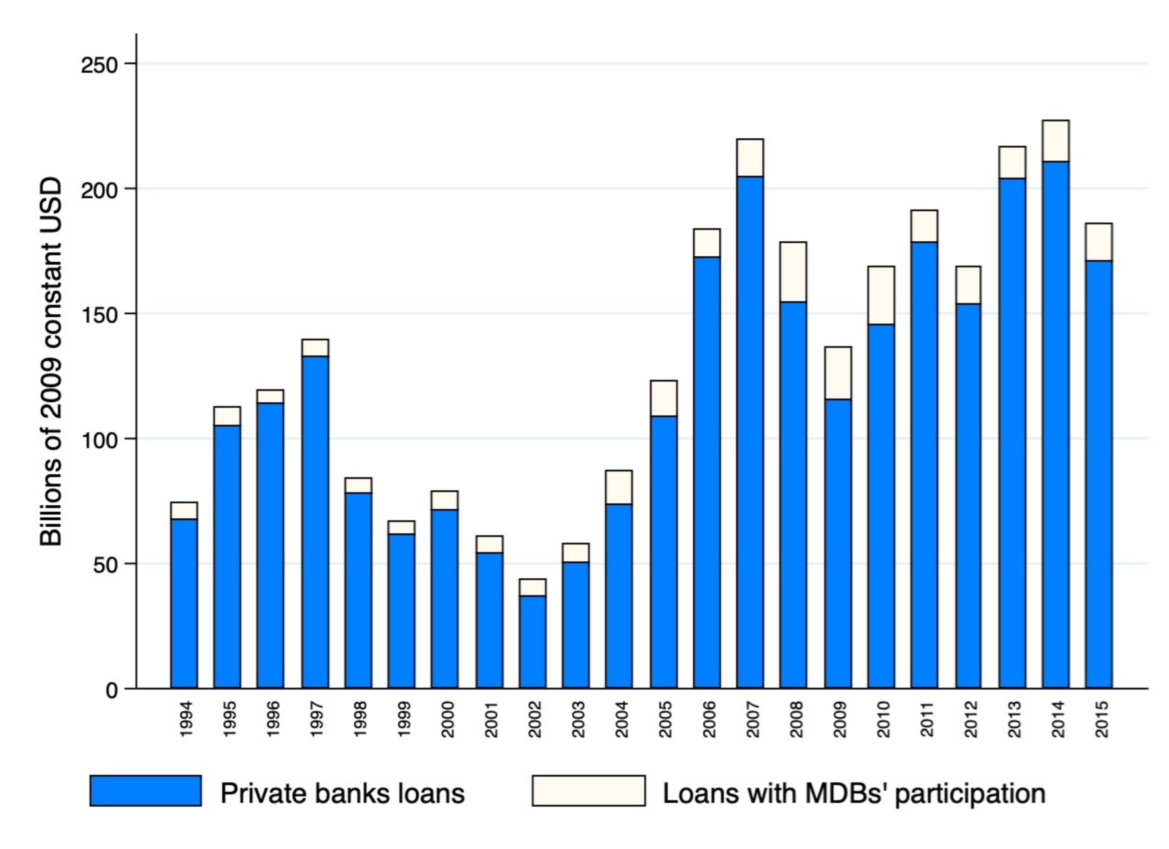
This paper looks at two interrelated questions. First, does the presence of an MDB in a syndicated loan affect loan terms, and especially the loan pricing? Second, does the involvement of MDBs mitigate the effect of borrower credit risk, translating into lower spreads? We examine loan terms of cross-border syndicated loans to address these questions. A key finding from our analysis is that MDBs' participation is associated with higher borrowing costs, indicating MDBs' greater willingness to finance high-risk projects that may not be financed by the private sector. Our results also show that MDBs' participation mitigates the effect of credit risk on loan spreads, as the effect of borrower riskiness on loan spreads is about one third lower in syndicated loans with at least an MDB than in comparable loans financed only by commercial banks. We find evidence confirming that MDBs tend to select loans for risky borrowers. Moreover, MDBs' participation is associated with longer loan maturities, implying MDBs' greater capacity to lend at longer tenure than the private sector, and smaller loan size, which cautions about the scope for a potential direct mobilization effect of MDBs. However, we observe that the role of MDB participation has more relevance during the post-crisis period, which could alleviate the observed flight to home effects in the cross-border syndicated loan market. Overall, our findings suggest that risk mitigation can be a channel through which MDBs—thanks to better information and monitoring and the extension of their preferred creditor status—can crowd in private investment to developing countries and emerging markets.

Figure 5.1. MDBs' Participation and Loan Pricing



Notes: The figure shows the all-in spread (in bps) of cross-border syndicated loans to developing countries. The chart is based on a sample of 7,038 deals to 106 countries and separates between deals with at least a multilateral and deals with only commercial banks. Data source: Dealogic Loan Analytics

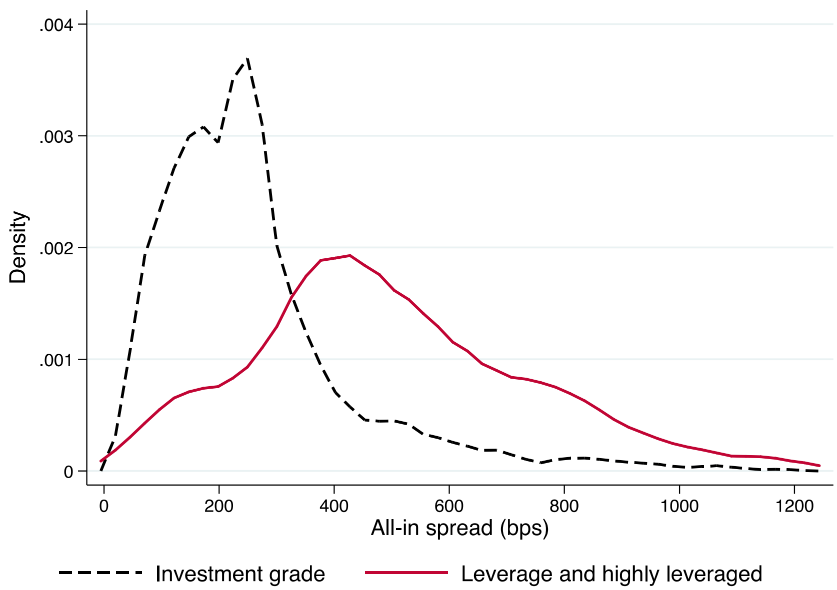
Figure 5.2. Cross-border Syndicated Lending to Developing Countries, in USD



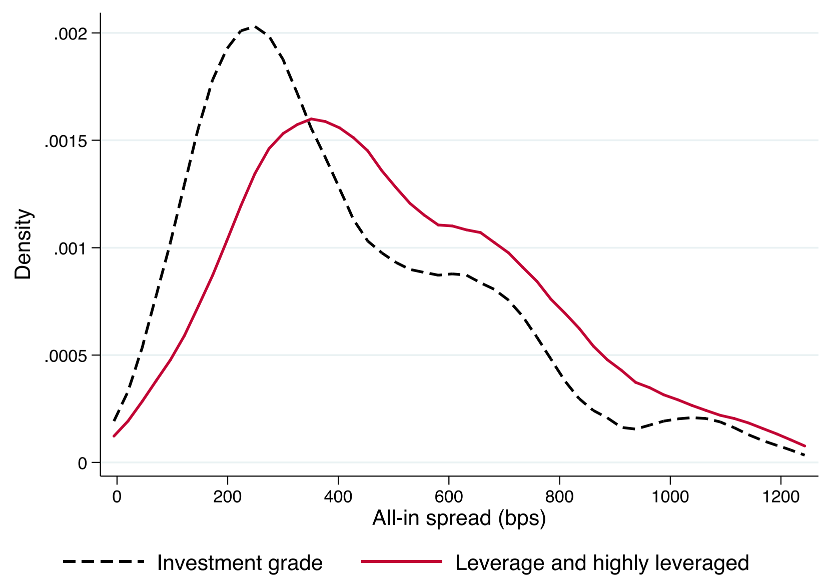
Notes: The figure shows the value in constant 2011 USD (billion) of cross-border syndicated lending to developing countries. The chart is based on a sample of 16,847 deals to 106 countries and separates between deals with at least a multilateral development bank in the syndicate and deals with only commercial banks. Data source: Dealogic Loan Analytics.

Figure 5.3. The De-risking Role of MDBs' Participation

(a) Deals without MDBs' participation



(b) Deals with MDBs' participation



Notes: The figure shows the all-in spread (in bps) of cross-border syndicated loans to developing countries. The chart is based on a sample of 7,038 deals to 106 countries and distinguishes between investment grade and leveraged and highly leveraged deals. Panel (a) presents the density for deals with only commercial banks, while panel (b) include deal with at least a multilateral development bank in the syndicate. Data source: Dealogic Loan Analytics.

Table 5.1. Descriptive statistics

Variable	Obs.	Mean	S.D.	Min	p25	p50	p75	Max
All-in spread	7038	351,5	232,08	37,5	180	286,6	475	1200
Spread	7345	168,9	116,24	17	85	135	225	625
Fees	7228	179,87	121,52	13	90	149	250	625
Deal value (USD million)	16847	177,03	438,64	0	21	65	170	18000
Log of deal value	16847	17,87	1,61	7,6	16,86	17,99	18,95	24
Maturity (months)	14915	52,6	46	1	12	36	72	360
MDB	16847	0,1	0,3	0	0	0	0	1
Number of tranches	16847	1,29	0,77	1	1	1	1	16
Term loan	16847	0,55	0,5	0	0	1	1	1
Public sector	16847	0,26	0,44	0	0	0	1	1
Risky	16847	0,25	0,43	0	0	0	1	1
Investment grade	16847	0,75	0,43	0	0	1	1	1
Leveraged	16847	0,21	0,41	0	0	0	0	1
Highly leveraged	16847	0,04	0,19	0	0	0	0	1
USD loan	16847	0,8	0,4	0	1	1	1	1
Euro loan	16847	0,08	0,28	0	0	0	0	1
Other currencies loan	16847	0,12	0,32	0	0	0	0	1
Deal with a guarantor	16847	0,23	0,42	0	0	0	0	1
Syndicate concentration	16847	0,45	0,38	0,01	0,12	0,27	1	1

Notes: The table presents the summary statistics of the variables employed in the analysis. The data is based on a sample of 16,847 deals to 107 countries granted during the period 1994-2015. All-in spread, spread, and fees are in basis points (bps). Deal value is expressed in USD million or in logarithm (log of deal value), while maturity is expressed in months. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Term loan is a dummy equal to 1 for term loans, and 0 for credit facilities. Public is a dummy equal to 1 if the loan is granted to public sector borrowers and 0 if the loan is to the private sector. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. The deal currency is classified in three categories—USD, Euro, and other currencies. Deal with a guarantor is a dummy equal to 1 if the loan has a guarantor, and 0 otherwise. Syndicate concentration is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. Data source: Dealogic Loan Analytics.

Table 5.2. Syndicated loan terms and MDBs' participation

	Deals					
	Commercial banks only		with MDBs' participation			
	Mean	Obs.	Mean	Obs.	Difference	t-test
Drawn return (bbs)	345,23	6601	446,32	437	101,09	***
Spread (bps)	165,77	6899	217,38	446	51,61	***
Fees (bps)	176,99	6776	223,08	452	46,09	***
Deal value (USD million)	179,36	15153	156,18	1694	-23,18	***
Maturity (month)	50,63	13967	81,62	948	30,99	***

Notes: The table shows the average values of loan terms for deals with only private banks and for those with at least one MDB involved in the syndication of the loan. The last columns show the difference and the results of a t-test for the equality of the means across the two samples. The sample period is 1994-2015. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.3. Loan pricing—All-in Spread

Dep. Var.: All-in spread	(1)	(2)	(3)	(4)	(5)	(6)
MDB	64.3813***	82.6265***	63.0023***	47.0927***	45.4043***	60.4875***
	(12.878)	(12.067)	(12.268)	(12.747)	(13.484)	(12.896)
Log of deal value	-3.1679	-20.1222**	-14.0197**	-17.4242***	-19.4645***	-13.9254**
	(9.384)	(7.834)	(5.124)	(4.770)	(4.844)	(5.491)
Number of tranches	21.2247***	15.1710**	11.8910**	13.9997***	13.8604***	11.0556*
	(6.220)	(5.604)	(5.100)	(4.329)	(3.967)	(5.810)
Maturity (in months)	0.4245*	0.7051***	0.7194***	0.7929***	0.7700***	0.6750***
	(0.245)	(0.144)	(0.196)	(0.208)	(0.192)	(0.195)
Leveraged	171.4569***	159.1101***	130.6725***	119.2904***	115.4159***	128.8962***
	(26.835)	(13.532)	(12.953)	(14.553)	(14.725)	(13.155)
Highly leveraged	426.2991***	465.8138***	388.7043***	368.8614***	364.6687***	381.8506***
	(26.631)	(22.611)	(20.519)	(19.645)	(20.382)	(20.362)
Term loan	28.6088**	38.1940***	40.2687***	35.3235***	36.6469***	44.2661***
	(10.880)	(11.120)	(9.874)	(9.830)	(9.288)	(10.116)
Public	-37.1885**	-49.7177***	-55.1404***	-61.9134***	-55.4730***	-54.5258***
	(14.774)	(15.938)	(11.868)	(13.996)	(12.748)	(11.547)
Euro	-32.9701	-10.1033	-43.8180**	-41.9157**	-49.6670***	-46.2936**
	(21.615)	(20.489)	(18.072)	(17.423)	(15.200)	(16.566)
Other currency	-43.7736***	-47.0924***	-22.9198*	-18.6712	-20.7171*	-28.8475***
	(13.914)	(11.180)	(11.222)	(11.836)	(11.382)	(10.052)
Deal with a guarantor	-12.4037	4.2185	-5.0795	-4.3782	-4.0366*	-1.2073
	(10.450)	(7.920)	(4.327)	(3.328)	(2.284)	(3.440)
Syndicate concentration	50.9959	-100.1885***	-84.8910***	-71.3918***	-71.1034***	-89.7323***
	(31.714)	(23.504)	(19.273)	(16.351)	(15.537)	(19.886)
Observations	6,958	6,958	6,945	6,726	6,724	6,871
R-squared	0.377	0.511	0.572	0.636	0.657	0.594
Country FE	No	No	Yes	-	-	-
Year FE	No	Yes	Yes	-	-	Yes
Industry FE	Yes	Yes	Yes	Yes	-	-
Country-Year FE	No	No	No	Yes	Yes	No
Industry-Year FE	No	No	No	No	Yes	No
Country-Industry FE	No	No	No	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is the all-in spread of the loan (spread plus fees) in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency is deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for the baseline model is 1994-2015, pre-crisis period is 1994-2007, and post-crisis period is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.4. Loan pricing—spreads and fees

Dep. Var.:	Spread		Fees	
	(1)	(2)	(3)	(4)
MDB	24.6882***	30.4665***	19.2753**	29.0835***
	(7.520)	(6.457)	(7.232)	(6.744)
Log of total deal value	-9.1183***	-5.8878**	-7.9939***	-6.3097**
	(2.380)	(2.821)	(2.560)	(2.527)
Number of tranches	5.9769**	3.2031	5.1261**	4.6951
	(2.320)	(3.129)	(2.099)	(2.877)
Maturity (in months)	0.2970***	0.2638**	0.4465***	0.4080***
	(0.084)	(0.097)	(0.081)	(0.096)
Leveraged	56.8459***	63.9924***	59.2183***	63.7570***
	(7.053)	(6.075)	(7.096)	(6.070)
Highly Leveraged	191.9646***	196.4676***	183.4410***	187.8040***
	(9.031)	(9.609)	(11.557)	(9.873)
Term loan	13.7201***	17.9561***	23.2939***	26.0868***
	(3.957)	(4.330)	(5.402)	(4.689)
Public	-24.8182***	-26.1130***	-26.9697***	-24.9886***
	(6.606)	(5.983)	(6.558)	(6.374)
Euro	-28.2780***	-23.0625**	-23.8665***	-22.8571**
	(9.040)	(8.453)	(6.759)	(8.287)
Other currency	-2.4392	-5.1525	-30.7537***	-35.3515***
	(4.182)	(3.972)	(9.409)	(9.620)
Deal with a guarantor	-3.8691*	-2.6657	-3.0508	-3.1794
	(2.209)	(3.098)	(3.984)	(2.614)
Syndicate concentration	-17.8288*	-26.5470**	-45.6909***	-52.0908***
	(8.609)	(9.872)	(7.570)	(7.341)
Observations	7,015	7,163	6,904	7,058
R-squared	0.667	0.601	0.581	0.527
Country FE	-	-	-	-
Year FE	-	Yes	-	Yes
Industry FE	-	-	-	-
Country-Year FE	Yes	No	Yes	No
Industry-Year FE	Yes	No	Yes	No
Country-Industry FE	No	Yes	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable in columns (1) and (2) is the loan spread, and in columns (3) and (4), the loan fees, all in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency is deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for the baseline model is 1994-2015, pre-crisis period is 1994-2007, and post-crisis period is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.5. Loan pricing, MDBs' participation, and de-risking

Dep. Var.:	All-in spread		Spread		Fees	
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	63.2427***	66.7475***	35.5429***	36.9337***	23.7166**	35.5153***
	(16.731)	(18.645)	(8.836)	(9.074)	(10.456)	(9.838)
MDB x Risky	-59.5944***		-34.5200***		-19.9740*	
	(15.758)		(8.760)		(9.928)	
MDB x High country risk		-41.2264*		-23.0643**		-29.9569**
		(21.403)		(9.097)		(10.559)
Risky	156.8479***	153.4012***	80.2366***	78.2758***	79.3607***	78.1482***
	(14.024)	(14.209)	(7.027)	(7.160)	(7.081)	(7.158)
Public	-60.2499***	-60.6424***	-27.8085***	-27.9600***	-29.2744***	-29.3085***
	(14.441)	(14.444)	(7.445)	(7.471)	(7.554)	(7.576)
Log of total deal value	-22.4576***	-22.4311***	-10.6135***	-10.5800***	-9.3501***	-9.3042***
	(6.233)	(6.571)	(2.960)	(2.941)	(3.074)	(3.044)
Number of tranches	14.5015***	14.4609***	6.3743**	6.3346**	5.4027*	5.3461*
	(4.858)	(4.959)	(2.776)	(2.696)	(2.697)	(2.694)
Maturity (in months)	0.7942***	0.8026***	0.3053**	0.3104***	0.4594***	0.4611***
	(0.190)	(0.189)	(0.120)	(0.105)	(0.087)	(0.086)
Term loan	40.8039***	40.5194***	16.0897***	15.8766***	25.2971***	25.2061***
	(9.980)	(9.796)	(4.418)	(4.395)	(5.557)	(5.668)
Euro	-53.0404***	-54.0893***	-30.0605***	-30.6123***	-25.4270***	-25.9831***
	(13.638)	(13.874)	(8.336)	(8.698)	(5.815)	(5.896)
Other currency	-17.9075*	-18.1721**	-0.8808	-1.0732	-29.6287***	-29.8034***
	(9.012)	(8.291)	(3.254)	(3.534)	(8.538)	(8.642)
Deal with a guarantor	-8.0794	-8.1275	-6.3980	-6.4428	-5.0483	-5.0242
	(5.777)	(5.470)	(3.867)	(3.859)	(4.991)	(4.936)
Syndicate concentration	-69.4635***	-69.2368***	-16.1830*	-15.9940*	-44.8760***	-44.7691***
	(17.283)	(17.458)	(8.953)	(8.902)	(8.177)	(8.108)
Observations	6,724	6,720	7,015	7,011	6,904	6,900
R-squared	0.613	0.612	0.615	0.614	0.542	0.541
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable in columns (1) and (2) is the all-in spread, while in columns (3) and (4) is the loan spread, and in columns (5) and (6) the loan fees, all in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. High country risk is a dummy equal to 1 for borrowers located in countries in the bottom half of the distribution of the country credit risk rating variable. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency are deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.6. Loan pricing—infrastructure and public sector lending

Dep. Var.:	All-in spread		Spread		Fees	
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	32.6194**	55.2291***	16.8229*	29.6921***	15.2647	23.4115**
	(13.452)	(15.972)	(9.400)	(8.684)	(10.065)	(8.938)
MDB x Infrastructure	65.6771**		39.6436***		20.2503	
	(24.455)		(13.057)		(12.892)	
MDB x Public		-52.9012*		-26.9046**		-23.0487
		(27.470)		(12.683)		(17.260)
Public	-55.7821***	-52.6893***	-25.0352***	-23.3909***	-27.0664	-25.7618***
	(14.144)	(12.947)	(7.803)	(6.527)	(28.233)	(6.831)
Log of total deal value	-19.3857***	-19.3024***	-9.0571*	-9.0305***	-7.9735***	-7.9240***
	(4.185)	(4.990)	(4.435)	(2.541)	(2.678)	(2.783)
Number of tranches	13.3279***	13.4676***	5.6675**	5.7731**	4.9704	4.9550**
	(3.665)	(3.910)	(2.402)	(2.317)	(6.395)	(2.131)
Maturity (in months)	0.7631	0.7644***	0.2929***	0.2946***	0.4450***	0.4444***
	(11.668)	(0.183)	(0.102)	(0.084)	(0.086)	(0.080)
Leveraged	115.7625***	115.6864***	57.0217***	56.9846***	59.3489***	59.3543***
	(14.779)	(14.859)	(7.069)	(7.133)	(10.379)	(7.187)
Highly leveraged	365.7773***	364.7117***	192.5244***	191.9777***	183.8045***	183.5388***
	(19.544)	(20.378)	(10.708)	(9.033)	(17.421)	(11.539)
Term loan	36.7073***	36.7087***	13.7693***	13.7451***	23.3062*	23.3199***
	(8.988)	(9.282)	(3.967)	(3.992)	(12.703)	(5.301)
Euro	-50.7689***	-48.1262***	-28.7797***	-27.5684***	-24.1892*	-23.2107***
	(15.265)	(15.642)	(9.544)	(9.070)	(11.915)	(7.100)
Other currency	-20.8641*	-20.8716*	-2.6496	-2.4437	-30.7971**	-30.7850***
	(12.058)	(11.455)	(5.854)	(4.415)	(11.095)	(9.462)
Deal with a guarantor	-3.8386	-3.6530	-3.7554	-3.6738*	-3.0041	-2.8723
	(3.396)	(2.146)	(2.317)	(2.065)	(5.940)	(3.850)
Syndicate concentration	-72.0942***	-71.1356***	-18.4231*	-17.8447**	-45.9849***	-45.7616***
	(15.437)	(15.541)	(9.388)	(8.531)	(8.297)	(7.709)
Observations	6,724	6,724	7,015	7,015	6,904	6,904
R-squared	0.657	0.657	0.668	0.667	0.581	0.581
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable in columns (1) and (2) is the all-in spread, while in columns (3) and (4) is the loan spread, and in columns (5) and (6) the loan fees, all in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Infrastructure is a dummy equal to 1 for infrastructure loans and 0 otherwise. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency are deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.7. Loan terms and MDBs' participation

Dep. Var.:	Deal value			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
MDB participation	-60.3707**	-69.5282**	-60.8277*	25.4464***	26.8113***	26.2506***
	(26.579)	(31.783)	(29.488)	(3.625)	(3.611)	(3.291)
Log of total deal value				5.7569***	5.7589***	5.9920***
				(0.551)	(0.736)	(0.781)
Maturity (in months)	0.8534**	0.8518**	0.8376**			
	(0.363)	(0.303)	(0.307)			
Number of tranches	100.4890***	105.5598***	104.6880***	6.8090***	6.7785***	6.1761***
	(14.899)	(17.922)	(15.758)	(1.173)	(1.213)	(1.120)
Leveraged	-7.7600	-20.4244	-9.3129	-9.3646***	-7.7714***	-9.4481***
	(16.529)	(25.968)	(18.072)	(1.661)	(1.293)	(1.352)
Highly leveraged	-43.4899	-53.8992**	-32.3138	-12.0614***	-6.8249***	-13.2790***
	(26.449)	(25.361)	(26.371)	(2.855)	(2.114)	(2.526)
Term loan	-32.8837***	-34.0574**	-32.2358***	9.8270***	9.3254***	10.2232***
	(11.277)	(12.082)	(10.433)	(1.858)	(2.014)	(1.735)
Public	7.9472	16.7582	12.6007	-0.1041	0.7064	0.5409
	(19.626)	(20.775)	(22.230)	(2.722)	(2.650)	(2.561)
Euro	-45.5481*	-34.9332	-29.1191	23.9950***	23.5877***	22.8421***
	(24.019)	(29.780)	(25.049)	(3.478)	(3.441)	(3.728)
Other currency	-21.1895	-14.0574	-20.1627	6.3406**	5.2172**	6.9646***
	(27.149)	(26.087)	(26.660)	(2.661)	(2.093)	(2.366)
Deal with a guarantor	-26.6927*	-28.2741	-24.4093	22.3603***	21.4241***	22.8271***
	(15.310)	(16.450)	(14.516)	(3.529)	(3.643)	(3.450)
Syndicate concentration	-301.4022***	-320.8541***	-295.4640***	12.4578***	14.7414***	10.1476***
	(42.126)	(47.778)	(44.016)	(3.482)	(3.655)	(3.529)
Observations	14,904	14,587	14,804	14,904	14,587	14,804
R-squared	0.169	0.221	0.197	0.366	0.441	0.408
Country FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	Yes	Yes	-	Yes
Industry FE	Yes	-	-	Yes	-	-
Country-Year FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	Yes	No	No	Yes	No
Country-Industry FE	No	No	Yes	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is, alternatively, loan size (in million of USD) in columns 1-3 and loan maturity (in months) in columns 4-6. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency are deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.8. The role of MDBs in the syndicated loan market—nearest neighbor matching

Dep. Var.:	All-in spread	Spread	Fees	Deal size	Maturity
	(1)	(2)	(3)	(4)	(5)
Matched	32.639**	30.274***	9.660	-83.297***	26.342***
	(16.516)	(7.746)	(9.693)	(22.771)	(3.378)
Unmatched	101.092***	51.616***	46.092***	-23.176**	30.995***
	(11.401)	(5.647)	(5.879)	(11.236)	(1.523)
# treated (MDB)	424	433	438	948	948
# controls	6534	6817	6707	13967	13967
Exact matching on:					
Loan type	Y	Y	Y	Y	Y
Nearest-neighbor matching on:					
Deal size	Y	Y	Y	N	Y
Maturity	Y	Y	Y	Y	N
Tranches	Y	Y	Y	Y	Y
Currency	Y	Y	Y	Y	Y
Riskiness	Y	Y	Y	Y	Y
Public sector	Y	Y	Y	Y	Y
Guarantor	Y	Y	Y	Y	Y
Concentration	Y	Y	Y	Y	Y
Industry	Y	Y	Y	Y	Y
Country	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y

Notes: This table presents results of nearest neighbor matching estimator using the set of covariates used in the baseline model 1. The dependent variable is, alternatively: all-in spread (column 1), spread (column 2), fees (column 3)–all in basis points,—deal value (in USD million, column 4), and maturity (in months, column 5)). The treatment variable—MDB—is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency are deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.9. De-risking—nearest neighbor matching

	MDB=0	MDB=1
	(1)	(2)
Matched	204.300**	130.163***
	(13.115)	(21.940)
Unmatched	237.780***	98.548***
	(5.100)	(24.390)
# treated (*Risky*)	2338	171
# controls	4196	252
Exact matching on:		
Loan type	Y	Y
Nearest-neighbor matching on:		
Deal size	Y	Y
Maturity	Y	Y
Tranches	Y	Y
Currency	Y	Y
Public sector	Y	Y
Guarantor	Y	Y
Concentration	Y	Y
Industry	Y	Y
Country	Y	Y
Year	Y	Y

Notes: This table presents results of nearest neighbor matching estimator using the set of covariates employed in the baseline model 1. The dependent variable is the all-in spread, in basis points. The treatment variable—Risky—is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency are deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.10. Robustness—sub-samples

Dep. Var.: All-in spread	Drop China		Drop CHN, IND, MEX		Drop small countries	
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	28.8218**	52.0012***	33.3147**	58.2688***	38.0142**	61.4145***
	(12.868)	(15.204)	(14.906)	(16.371)	(14.833)	(16.738)
MDB x Risky		-53.3596***		-57.3307***		-59.4955***
		(14.986)		(14.411)		(15.377)
Risky	148.3222***	151.5920***	144.9960***	148.9809***	153.5144***	156.9028***
	(14.798)	(14.571)	(16.457)	(16.157)	(14.370)	(14.101)
Public	-76.2528***	-75.6814***	-65.0072***	-64.3312***	-61.4082***	-60.7715***
	(14.423)	(14.400)	(18.981)	(18.911)	(14.318)	(14.449)
Log of total deal value	-26.1543***	-26.0798***	-26.2144***	-26.1533***	-22.2080***	-22.1277***
	(6.880)	(6.844)	(8.524)	(8.526)	(6.295)	(6.235)
Number of tranches	15.0259**	14.9863**	12.0693**	12.0363**	14.7966***	14.7134***
	(5.606)	(5.904)	(4.721)	(4.865)	(4.828)	(4.859)
Maturity (in months)	0.9237**	0.9111***	0.8082***	0.7980**	0.7979***	0.7873***
	(0.360)	(0.231)	(0.236)	(0.373)	(0.199)	(0.192)
Term loan	36.5035***	36.9258***	31.9148***	32.3683***	40.1377***	40.5928***
	(9.445)	(10.202)	(10.701)	(11.355)	(9.586)	(9.975)
Euro	-43.2781***	-42.8031***	-29.8211**	-29.0196**	-53.4823***	-53.3007***
	(8.018)	(7.535)	(13.467)	(13.006)	(14.122)	(13.945)
Other currency	-22.2652	-22.1934	-18.9672	-19.1542	-17.9624**	-17.9396*
	(14.380)	(14.623)	(17.866)	(17.982)	(8.212)	(9.129)
Deal with a guarantor	-3.7658	-3.6201	-2.3705	-2.2501	-8.0018	-7.8756
	(6.676)	(7.247)	(8.615)	(9.845)	(5.244)	(5.705)
Syndicate concentration	-77.0229**	-76.7737**	-75.7580**	-75.5126**	-69.1756***	-68.8479***
	(29.914)	(29.955)	(30.058)	(30.088)	(17.411)	(17.450)
Observations	5,229	5,229	3,975	3,975	6,645	6,645
R-squared	0.616	0.617	0.633	0.633	0.604	0.605
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable is the all-in spread, in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. The excluded category for currency are deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

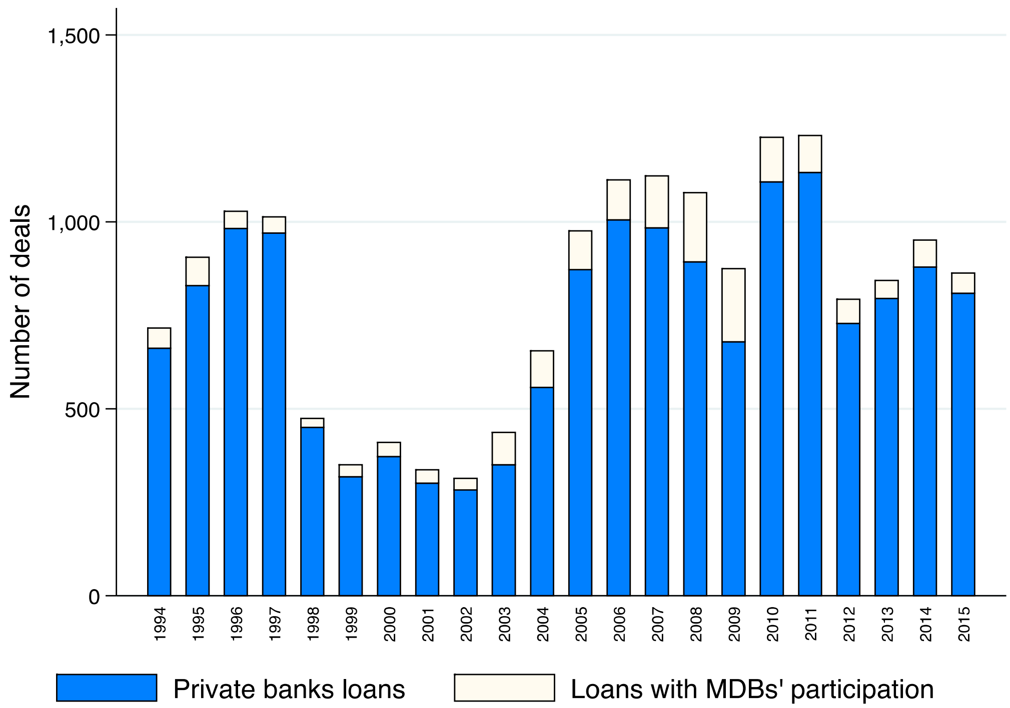
Table 5.11. Robustness—credit facilities versus term loans

Dep. Var.: All-in spread	Credit facilities			Term loans		
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	106.4106**	113.4181**	206.7033***	19.5031	41.1421**	49.2923**
	(43.423)	(54.335)	(64.247)	(15.899)	(18.428)	(18.448)
MDB x Risky		-25.5953			-51.2906***	
		(73.249)			(16.573)	
MDB x High country risk			-165.2530*			-45.5461**
			(83.826)			(18.642)
Risky	149.7427***	150.2758***	149.3539***	153.3471***	156.8117***	153.1936***
	(20.288)	(20.444)	(20.131)	(15.247)	(15.313)	(15.114)
Public	-52.5944**	-52.3783**	-50.6259**	-54.6101***	-54.0227***	-54.3417***
	(19.769)	(19.902)	(20.744)	(12.700)	(13.383)	(12.733)
Log of total deal value	-19.8625***	-19.9180***	-19.6612***	-26.3244***	-26.2040***	-26.0855***
	(6.659)	(5.970)	(6.531)	(8.446)	(8.330)	(8.390)
Number of tranches	18.7399	18.6051	19.3758	12.6993***	12.6714***	12.5354**
	(16.073)	(16.138)	(16.066)	(4.418)	(4.309)	(4.686)
Maturity (in months)	0.0813	0.0773	0.0590	1.0784***	1.0702***	1.0788***
	(0.223)	(0.194)	(0.208)	(0.322)	(0.285)	(0.333)
Euro	-102.9652***	-103.2945***	-103.1462***	-31.1473**	-30.4623*	-32.7674**
	(24.253)	(24.397)	(24.481)	(14.538)	(15.129)	(14.695)
Other currency	-15.6564	-15.7240	-15.7216	-19.5721	-19.3091	-19.3440
	(10.180)	(10.574)	(10.674)	(12.050)	(12.221)	(12.192)
Deal with a guarantor	-10.9784	-10.7800	-9.5871	-4.8177	-4.9510	-4.9550
	(13.081)	(16.239)	(13.250)	(6.749)	(6.877)	(6.696)
Syndicate concentration	-40.2985**	-40.7230**	-39.7879*	-83.6439***	-82.7082***	-83.1168***
	(17.108)	(16.979)	(19.364)	(25.034)	(24.672)	(25.036)
Observations	1,941	1,941	1,941	4,611	4,611	4,609
R-squared	0.659	0.659	0.661	0.635	0.636	0.635
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable is the all-in spread, in basis points (bps). Columns 1-3 refer to the sub-sample of credit facilities, while columns 4-6 to that of term loans. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. High country risk is a dummy equal to 1 for borrowers located in countries in the bottom half of the distribution of teh country credit risk rating variable. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency are deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

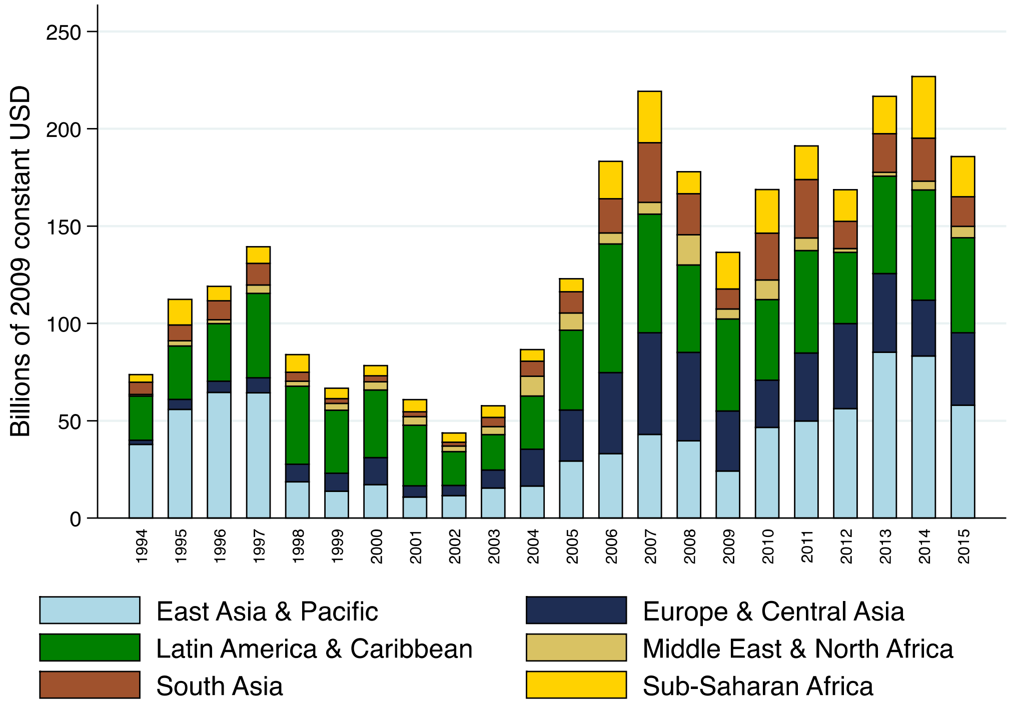
Appendix

Figure 5.A1. Cross-border syndicated lending to emerging and developing Countries (Number of deals)



Notes: The figure shows the number of cross-border syndicated loan deals to developing countries. The chart is based on a sample of 16,847 deals to 107 countries and separates between deals with at least a multilateral development bank in the syndicate and deals with only commercial banks. Data source: Dealogic Loan Analytics.

Figure 5.A2. Cross-border syndicated lending to emerging and developing countries, by region, in USD



Notes: The figure shows the value in constant 2011 USD (billion) of cross-border syndicated lending to developing countries (see Table 5.A1 for the list of countries). The chart is based on a sample of 16,847 deals to 107 countries and separates between deals according to the region of the borrower, according to the World Bank classification. Data source: Dealogic Loan Analytics.

Table 5.A1. Syndicated loan deals and MDBs' participation across sectors

Country	# deals	with MDBs	LIC	Country	# deals	with MDBs	LIC
Afghanistan	1	1	1	Lebanon	24	5	0
Albania	14	11	0	Lesotho	1	1	1
Algeria	57	4	0	Liberia	54	1	1
Angola	60	7	0	Libya	4	2	0
Armenia	39	28	0	Macedonia	22	12	0
Azerbaijan	132	51	0	Madagascar	3	1	1
Bangladesh	53	2	1	Malawi	3	1	1
Belarus	65	21	0	Malaysia	624	5	0
Belize	1	1	0	Maldives	8	3	1
Benin	6	0	1	Mali	16	3	1
Bhutan	2	1	1	Mauritania	4	1	1
Bolivia	20	10	1	Mauritius	18	1	0
Bosnia and Herzegov..	28	27	0	Mexico	1.369	37	0
Botswana	7	1	0	Moldova	40	38	1
Brazil	1.865	76	0	Mongolia	33	15	1
Bulgaria	132	70	0	Montenegro	9	7	0
Burkina Faso	0	9	1	Morocco	60	5	0
Cambodia	8	2	1	Mozambique	21	8	1
Cameroon	21	5	1	Myanmar	4	0	1
Cape Verde	1	0	1	Namibia	10	3	0
Chad	4	2	1	Nepal	4	2	1
China	3.140	52	0	Nicaragua	9	5	1
Colombia	274	30	0	Niger	2	1	1
Congo	8	1	1	Nigeria	171	32	1
Congo, Democratic R..	10	3	1	Pakistan	231	47	0
Costa Rica	50	8	0	Panama	152	9	0
Cote D'Ivoire (Ivor..	27	8	1	Paraguay	12	1	0
Cuba	13	0	0	Peru	258	21	0
Djibouti	2	0	1	Philippines	436	21	0
Ecuador	24	3	0	Romania	232	112	0
Egypt	190	52	0	Rwanda	6	5	1
El Salvador	43	4	0	Senegal	20	5	1
Eritrea	2	0	1	Serbia	64	46	0
Ethiopia	14	5	1	Sierra Leone	2	1	1
Fiji	1	0	0	South Africa	388	39	0
Gabon	5	2	0	Sri Lanka	35	8	0
Georgia	39	30	0	Sudan	2	1	1

Ghana	88	17	1	Syria	1	0	0
Grenada	2	0	1	Tajikistan	15	15	1
Guatemala	30	3	0	Tanzania	23	6	1
Guinea	7	1	1	Thailand	873	40	0
Guyana	1	1	1	Togo	3	2	1
Haiti	5	3	1	Tunisia	46	10	0
Honduras	16	2	1	Turkey	1.032	150	0
India	1.423	81	0	Turkmenistan	10	2	0
Indonesia	1.210	38	0	Uganda	18	12	1
Iran	110	2	0	Ukraine	349	108	0
Iraq	7	3	0	Uzbekistan	55	17	1
Jamaica	31	6	0	Vanuatu	1	1	1
Jordan	41	12	0	Vietnam	243	20	1
Kazakhstan	346	65	0	Yemen	9	2	1
Kenya	35	13	1	Zambia	48	14	1
Kyrgyzstan	21	19	1	Zimbabwe	14	4	1
Laos	16	2	1				

Notes: The table shows, by country, the total number of loan deals, as well as only those with at least one MDB involved in the syndication of the loan. The "LIC" column identifies low-income countries. The sample consists of 16,847 deals to 107 countries over the period 1994-2015. Data sources: Dealogic Loan Analytics.

Table 5.A2. Syndicated loan deals and MDBs' participation across industry

Industry	# deals	%	of which, with MDB	%
Finance	5586	0,33	657	0,39
Government	30	0,00	3	0,00
Oil & Gas	1413	0,08	124	0,07
Agriculture	389	0,02	53	0,03
Log of deal value	1290	0,08	100	0,06
Infrastructure	3791	0,23	436	0,26
Manufacturing	3417	0,20	237	0,14
Mining \& Metals	462	0,03	30	0,02
Services	469	0,03	54	0,03
Total	16847	1,00	1.694	1,00

Notes: The table shows, by sector, presents the total number of loan deals, as well as only those with at least one MDB involved in the syndication of the loan. The sample period is 1994-2015. Data sources: Dealogic Loan Analytics.

Table 5.A3. Robustness—alternative clustering

Dep. Var.: All-in spread	(1)	(2)	(3)	(4)	(5)	(6)
MDB	64.3813***	82.6265***	63.0023***	47.0927***	45.4043***	60.4875***
	(14.809)	(12.968)	(13.315)	(14.929)	(15.817)	(13.817)
Log of deal value	-3.1679	-20.1222***	-14.0197***	-17.4242***	-19.4645***	-13.9254***
	(6.373)	(6.348)	(4.351)	(4.267)	(4.200)	(4.687)
Number of tranches	21.2247***	15.1710**	11.8910**	13.9997**	13.8604***	11.0556*
	(5.655)	(5.754)	(5.473)	(5.309)	(4.881)	(6.307)
Maturity (in months)	0.4245**	0.7051***	0.7194***	0.7929***	0.7700***	0.6750***
	(0.205)	(0.135)	(0.166)	(0.188)	(0.165)	(0.173)
Leveraged	171.4569***	159.1101***	130.6725***	119.2904***	115.4159***	128.8962***
	(21.482)	(10.437)	(9.482)	(12.158)	(12.683)	(9.973)
Highly leveraged	426.2991***	465.8138***	388.7043***	368.8614***	364.6687***	381.8506***
	(22.863)	(23.046)	(20.475)	(19.395)	(19.486)	(19.860)
Term loan	28.6088***	38.1940***	40.2687***	35.3235***	36.6469***	44.2661***
	(9.141)	(8.855)	(7.255)	(7.774)	(6.996)	(6.991)
Public	-37.1885**	-49.7177***	-55.1404***	-61.9134***	-55.4730***	-54.5258***
	(14.914)	(15.098)	(11.116)	(13.349)	(12.317)	(10.814)
Euro	-32.9701	-10.1033	-43.8180***	-41.9157**	-49.6670***	-46.2936***
	(20.680)	(18.823)	(15.760)	(17.746)	(17.249)	(15.358)
Other currency	-43.7736***	-47.0924***	-22.9198*	-18.6712	-20.7171	-28.8475**
	(14.346)	(12.156)	(11.774)	(13.016)	(12.725)	(10.888)
Deal with a guarantor	-12.4037	4.2185	-5.0795	-4.3782	-4.0366	-1.2073
	(10.438)	(8.822)	(5.905)	(5.320)	(4.878)	(5.135)
Syndicate concentration	50.9959**	-100.1885***	-84.8910***	-71.3918***	-71.1034***	-89.7323***
	(23.876)	(19.155)	(17.113)	(13.903)	(14.727)	(18.300)
Observations	6,958	6,958	6,945	6,726	6,724	6,871
R-squared	0.377	0.511	0.572	0.636	0.657	0.594
Country FE	No	No	Yes	-	-	-
Year FE	No	Yes	Yes	-	-	Yes
Industry FE	Yes	Yes	Yes	Yes	-	-
Country-Year FE	No	No	No	Yes	Yes	No
Industry-Year FE	No	No	No	No	Yes	No
Country-Industry FE	No	No	No	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is the all-in spread of the loan (spread plus fees) in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency are deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A4. Loan terms and MDBs' participation—sub-sample

Dep. Var.:	Deal value			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
MDB participation	-62.4624**	-40.5714	-53.8281**	14.5607***	15.3793***	15.1415***
	(25.515)	(24.673)	(24.782)	(4.565)	(4.782)	(4.211)
Log of total deal value				4.9152***	4.9025***	4.9171***
				(1.271)	(1.305)	(1.318)
Maturity (in months)	0.5101	0.4325	0.4724			
	(0.795)	(0.340)	(0.464)			
Number of tranches	100.6972***	106.3152***	102.9520***	8.0647***	8.1159***	7.4853***
	(18.635)	(25.339)	(21.774)	(1.331)	(1.432)	(1.206)
Leveraged	-33.8663	-22.2072	-23.1663	-8.5443***	-6.4281***	-8.1321***
	(29.445)	(29.830)	(28.425)	(1.410)	(0.829)	(1.529)
Highly leveraged	-66.1767**	-59.8099**	-36.3564	-9.6137***	-3.9710	-9.8733***
	(28.490)	(28.461)	(25.514)	(2.774)	(2.440)	(2.757)
Term loan	-42.2275**	-40.3435*	-32.7483*	8.2726***	8.1629***	8.6875***
	(18.837)	(21.351)	(16.869)	(1.971)	(2.119)	(1.969)
Public	20.6425	19.9621	11.9584	-1.7565	0.1067	-1.2744
	(27.860)	(26.575)	(32.538)	(1.885)	(1.830)	(2.274)
Euro	-30.5970	-43.1866***	-14.6425	12.6409***	9.8514***	10.6611***
	(22.389)	(13.880)	(26.313)	(2.832)	(3.072)	(2.820)
Other currency	33.8168	44.1650	38.1199	5.5948**	4.4007**	6.0950***
	(44.860)	(44.109)	(42.447)	(2.325)	(1.964)	(1.956)
Deal with a guarantor	11.6142	1.5985	12.2930	6.1454**	5.9179***	6.4195***
	(18.432)	(19.360)	(17.460)	(2.182)	(1.768)	(2.023)
Syndicate concentration	-389.6866***	-361.0716***	-387.4728***	17.3857***	19.7839***	14.5581***
	(69.103)	(84.887)	(71.003)	(3.178)	(3.127)	(2.807)
Observations	6,945	6,724	6,871	6,945	6,724	6,871
R-squared	0.211	0.296	0.254	0.383	0.476	0.427
Country FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	Yes	Yes	-	Yes
Industry FE	Yes	-	-	Yes	-	-
Country-Year FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	Yes	No	No	Yes	No
Country-Industry FE	No	No	Yes	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is the loan maturity (in months). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). In columns (7) and (8) risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. The excluded category for currency are deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period is 1994-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A5. Loan pricing -All-in Spread- before and after the global financial crisis

Dep. Var.: All-in spread	Baseline (1)	pre-crisis (2)	post-crisis (3)
MDB	60.4875***	31.1891***	59.8984**
	(12.896)	(6.976)	(28.793)
Log of deal value	-13.9254**	-6.0140**	-12.8463***
	(5.491)	(2.357)	(4.194)
Number of tranches	11.0556*	3.1771	2.7258
	(5.810)	(3.185)	(8.288)
Maturity (in months)	0.6750***	0.2626***	0.3526*
	(0.195)	(0.075)	(0.198)
Leveraged	128.8962***	63.8751***	176.6569***
	(13.155)	(4.339)	(13.253)
Highly leveraged	381.8506***	197.3579***	285.7769***
	(20.362)	(9.883)	(43.586)
Term loan	44.2661***	17.4289***	82.6459***
	(10.116)	(3.182)	(13.470)
Public	-54.5258***	-25.7066***	-62.2627***
	(11.547)	(5.168)	(13.743)
Euro	-46.2936**	-24.8484***	-66.2024***
	(16.566)	(6.015)	(23.765)
Other currency	-28.8475***	-5.3933	-51.6858**
	(10.052)	(3.515)	(20.752)
Deal with a guarantor	-1.2073	-2.1246	10.8933
	(3.440)	(3.466)	(17.259)
Syndicate concentration	-89.7323***	-27.5409***	-101.5784***
	(19.886)	(7.959)	(24.178)
Observations	6,871	3732	1,825
R-squared	0.594	0.582	0.568
Country FE	-	-	-
Year FE	Yes	Yes	Yes
Industry FE	-	-	-
Country-Year FE	No	No	No
Industry-Year FE	No	No	No
Country-Industry FE	Yes	Yes	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is the all-in spread of the loan (spread plus fees) in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). The excluded category for currency is deals in USD. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for the baseline model is 1994-2015, pre-crisis period is 1994-2007, and post-crisis period is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A61. Loan pricing, MDBs' participation, and de-risking- Pre-crisis

Dep. Var.:	Pre-crisis period (1994-2007)					
	All-in spread		Spread		Fees	
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	72.3207***	73.6157***	32.9305***	31.1386***	27.4975**	36.4468***
	(12.486)	(18.993)	(6.026)	(9.361)	(9.721)	(11.298)
MDB x Risky	-71.0625***		-34.2480***		-26.9278***	
	(13.348)		(8.092)		(8.376)	
MDB x High country risk		-42.8147*		-17.3005		-28.2166**
		(24.013)		(11.875)		(12.153)
Risky	148.3226***		76.8279***		74.8342***	
	(15.950)		(7.850)		(7.842)	
Public	-54.2209***	-54.7302***	-24.3684***	-24.5996***	-29.3072***	-29.4288***
	(15.306)	(15.524)	(7.639)	(7.769)	(7.919)	(8.016)
Log of total deal value	-26.2580***	-26.3264***	-13.1425***	-13.1563***	-11.0811***	-11.0815***
	(6.474)	(6.541)	(2.990)	(3.148)	(2.992)	(2.904)
Number of tranches	16.4501***	16.5741***	7.6216**	7.6646**	7.5870**	7.6410**
	(4.836)	(4.528)	(2.993)	(2.892)	(2.610)	(2.550)
Maturity (in months)	0.8810***	0.8948***	0.3343*	0.3398***	0.5444***	0.5492***
	(0.190)	(0.179)	(0.161)	(0.077)	(0.102)	(0.096)
Term loan	36.2858***	35.8767***	13.3315***	13.1324***	24.0692***	23.8976***
	(9.736)	(9.205)	(4.097)	(3.976)	(5.665)	(5.697)
Euro	-36.2324**	-37.4047**	-23.8409***	-24.2886***	-18.9166*	-19.5964*
	(15.816)	(15.053)	(7.287)	(7.055)	(9.196)	(9.099)
Other currency	-13.7022	-13.6699	4.6735	4.6711	-15.5494	-15.6673
	(13.212)	(12.949)	(4.544)	(4.641)	(10.152)	(10.324)
Deal with a guarantor	-10.1229	-10.0537	-8.1108	-8.0828	-3.0539	-2.9519
	(9.161)	(8.974)	(4.907)	(4.907)	(5.349)	(5.323)
Syndicate concentration	-66.1114***	-66.4738***	-12.3426	-12.4886	-42.5055***	-42.7357***
	(17.569)	(17.553)	(8.746)	(8.837)	(9.787)	(9.550)
Observations	3732	3732	4,073	4,069	3,999	3,995
R-squared	0.593	0.591	0.598	0.596	0.522	0.520
Country FE	-	-	-	-	-	-
Year FE	-	-	-	-	-	-
Industry FE	-	-	-	-	-	-
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable in columns (1) and (2) is the all-in spread, while in columns (3) and (4) is the loan spread, and in columns (5) and (6) the loan fees, all in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. High country risk is a dummy equal to 1 for borrowers located in countries in the bottom half of the distribution of the country credit risk rating variable. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency is deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for pre-crisis is 1994-2007, and for post-crisis is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A62. Loan pricing, MDBs' participation, and de-risking- Post-crisis

	Post-crisis period (2008-2015)					
Dep. Var.:	All-in spread		Spread		Fees	
	(1)	(2)	(3)	(4)	(5)	(6)
MDB	70.1350***	63.9798**	59.8984**	53.9574***	6.4292	50.9744**
	(19.936)	(17.697)	(28.793)	(9.173)	(17.761)	(17.957)
MDB x Risky	-60.0114**		-36.2416***		53.5643	
	(21.875)		(12.700)		(51.202)	
MDB x High country risk		-50.9632***		-51.6858**		-42.4925
		(11.356)		(20.752)		(41.358)
Risky	183.3353***		91.9140***		93.4410***	
	(13.134)		(6.601)		(8.333)	
Public	-64.4124**	-64.0938**	-32.0153**	-32.0360**	-25.2476**	-25.0078*
	(20.014)	(20.740)	(10.539)	(10.993)	(10.301)	(11.074)
Log of total deal value	-14.3513	-14.4011	-6.9920	-6.9819	-6.7969	-6.8377
	(10.167)	(8.746)	(4.466)	(4.175)	(5.638)	(6.044)
Number of tranches	2.3306	2.7216	0.6306	0.6441	-2.1603	-1.9275
	(11.183)	(11.696)	(5.745)	(5.750)	(6.464)	(6.766)
Maturity (in months)	0.5437	0.5490	0.2160	0.2182	0.2366	0.2384
	(0.601)	(0.585)	(0.226)	(0.223)	(0.198)	(0.219)
Term loan	52.7565**	52.3373**	24.4828*	24.3491*	29.4992**	29.2387**
	(16.852)	(16.566)	(12.149)	(11.937)	(10.183)	(9.831)
Euro	-72.5099**	-73.1034**	-38.7836**	-38.9933**	-32.4479**	-32.8721*
	(24.337)	(24.455)	(15.543)	(15.235)	(13.058)	(13.776)
Other currency	-35.2097**	-34.2452**	-19.2455*	-19.3124*	-61.2101***	-60.5618***
	(11.961)	(12.317)	(9.127)	(8.866)	(6.684)	(7.252)
Deal with a guarantor	-2.9971	-3.3763	-2.4019	-2.4689	-13.2795	-13.5088
	(16.937)	(16.415)	(5.967)	(6.860)	(9.222)	(8.841)
Syndicate concentration	-73.7909*	-72.5109*	-24.8935	-24.6942	-53.6084**	-52.9244**
	(31.723)	(36.176)	(14.484)	(16.489)	(18.907)	(19.215)
Observations	1,810	1,810	1,939	1,939	1,890	1,890
R-squared	0.595	0.595	0.594	0.594	0.542	0.541
Country FE	-	-	-	-	-	-
Year FE	-	-	-	-	-	-
Industry FE	-	-	-	-	-	-
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	No	No	No	No	No	No

Notes: The table presents OLS estimates of model 1. The dependent variable in columns (1) and (2) is the all-in spread, while in columns (3) and (4) is the loan spread, and in columns (5) and (6) the loan fees, all in basis points (bps). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Risky is a dummy equal to 1 if the loan is classified as leveraged or highly leveraged, and 0 is the loan has investment grade. High country risk is a dummy equal to 1 for borrowers located in countries in the bottom half of the distribution of the country credit risk rating variable. Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency is deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for pre-crisis is 1994-2007, and for post-crisis is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A7.1. Loan Terms and MDBs' Participation-pre-crisis

Dep. Var.:	Pre-crisis period (1994-2007)					
	Deal value			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
MDB participation	-44.2198*	-54.6933**	-46.2228**	18.8417***	20.4311***	20.1859***
	(22.553)	(23.936)	(19.992)	(4.567)	(4.860)	(4.639)
Log of total deal value				5.6116***	5.8785***	5.7102***
				(0.965)	(1.091)	(1.224)
Maturity (in months)	0.3941**	0.4193**	0.3985**			
	(0.173)	(0.147)	(0.176)			
Number of tranches	81.6171***	85.0640***	80.8535***	8.4741***	8.1932***	7.6381***
	(8.698)	(10.600)	(8.018)	(1.280)	(1.329)	(1.164)
Leveraged	11.9574	9.6149	16.6214	-11.6228***	-10.2094***	-10.4188***
	(22.370)	(23.743)	(23.128)	(1.248)	(1.423)	(1.132)
Highly leveraged	-35.3105	-36.1859	-21.1272	-11.7508***	-8.0029***	-12.1766***
	(21.025)	(23.491)	(20.629)	(2.025)	(2.276)	(1.924)
Term loan	-25.9859**	-24.2979**	-23.7925**	6.9855***	6.5301***	7.6713***
	(9.348)	(10.657)	(10.089)	(1.891)	(1.787)	(1.785)
Public	-10.4422	-11.6926	-18.9467	2.1326	2.2438	3.1511
	(16.154)	(18.474)	(21.132)	(2.371)	(2.287)	(2.254)
Euro	-16.3508	-20.1163	-6.0453	22.3234***	21.7739***	21.5119***
	(11.342)	(13.689)	(13.913)	(4.633)	(5.479)	(4.959)
Other currency	-3.4635	-2.4300	-0.6835	8.4980**	7.9648***	8.7936***
	(17.927)	(20.111)	(16.501)	(3.108)	(2.594)	(2.720)
Deal with a guarantor	-5.1623	-10.7112	-2.8780	18.3784***	17.8946***	18.2862***
	(15.546)	(18.086)	(13.375)	(4.293)	(4.291)	(3.988)
Syndicate concentration	-246.7451***	-251.3750***	-247.3754***	13.1254***	13.5986**	11.6906**
	(54.362)	(55.926)	(56.191)	(4.158)	(4.639)	(4.439)
Observations	8,720	8,534	8,644	8,720	8,534	8,644
R-squared	0.144	0.179	0.178	0.346	0.416	0.398
Country FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	Yes	Yes	-	Yes
Industry FE	Yes	-	-	Yes	-	-
Country-Year FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	Yes	No	No	Yes	No
Country-Industry FE	No	No	Yes	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is, alternatively, loan size (in million of USD) in columns 1-3 and loan maturity (in months) in columns 4-6. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency is deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for pre-crisis is 1994-2007, and for post-crisis is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A7.2. Loan Terms and MDBs' Participation-post-crisis

Dep. Var.:	Post-crisis period (2008-2015)					
	Deal value			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
MDB participation	-98.2892	-101.6901	-67.7133	36.7068***	36.8812***	35.0228***
	(74.344)	(84.240)	(85.949)	(5.894)	(5.848)	(5.900)
Log of total deal value				5.5779***	5.5774***	5.9454***
				(1.002)	(1.163)	(1.020)
Maturity (in months)	1.3925**	1.3447**	1.3899**			
	(0.434)	(0.466)	(0.543)			
Number of tranches	123.1051***	131.1922***	130.4448***	4.7255**	5.2869**	4.6878**
	(18.644)	(25.024)	(19.343)	(1.501)	(1.774)	(1.679)
Leveraged	-56.6359	-68.3634	-72.3674	-3.8937	-3.7954	-5.6354*
	(40.701)	(51.708)	(42.674)	(2.510)	(2.349)	(2.398)
Highly leveraged	-194.4418***	-175.3283***	-161.7918***	-4.3741	-7.1026**	-7.0011*
	(43.597)	(42.772)	(41.575)	(2.753)	(2.497)	(3.109)
Term loan	-50.9002*	-55.5719**	-50.1180*	13.6270***	14.3267***	12.9060***
	(23.832)	(22.611)	(23.327)	(3.237)	(3.413)	(3.165)
Public	42.2123	54.5506*	61.9932**	-0.6244	0.1374	-1.8832
	(27.553)	(23.157)	(22.726)	(3.340)	(3.824)	(3.369)
Euro	-83.9791	-49.2249	-51.4503	22.4096***	24.0089***	21.2285***
	(46.092)	(53.551)	(47.629)	(2.914)	(2.905)	(3.132)
Other currency	-41.3516	-29.6144	-33.0482	2.3434	2.9016	3.4248
	(35.510)	(32.811)	(37.970)	(3.846)	(3.517)	(3.927)
Deal with a guarantor	-57.4058	-53.8007	-53.5093	27.3019***	26.9430***	27.7397***
	(34.842)	(34.927)	(35.379)	(3.801)	(3.951)	(3.888)
Syndicate concentration	-395.8791***	-412.4765***	-374.9902***	15.4836**	16.8534**	11.8001*
	(59.373)	(69.388)	(66.114)	(4.970)	(5.385)	(4.828)
Observations	6,177	6,060	6,100	6,177	6,060	6,100
R-squared	0.193	0.242	0.237	0.437	0.478	0.483
Country FE	Yes	-	-	Yes	-	-
Year FE	Yes	-	Yes	Yes	-	Yes
Industry FE	Yes	-	-	Yes	-	-
Country-Year FE	No	Yes	No	No	Yes	No
Industry-Year FE	No	Yes	No	No	Yes	No
Country-Industry FE	No	No	Yes	No	No	Yes

Notes: The table presents OLS estimates of model 1. The dependent variable is, alternatively, loan size (in million of USD) in columns 1-3 and loan maturity (in months) in columns 4-6. MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. Leveraged and highly leveraged deals are expressed with reference to investment grade ones (the excluded category). Public is a dummy equal to 1 for deals to public sector borrowers and 0 for private sector ones. The excluded category for currency is deals in USD. The concentration of the syndicated loan is measured by the Herfindahl-Hirschman Index (HHI) calculated on the share of each bank in the loan. The data are at the deal level. The sample period for pre-crisis is 1994-2007, and for post-crisis is 2008-2015. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

Table 5.A8. MDB participation and lending to risky borrowers

Dep. Var.: Risky =1	Baseline	Pre-crisis	Post-crisis
MDB	0,19***	0,16***	0,23***
	-0,034	0,026	0,041
Observations	6,871	3,732	1,825
Observations=1	1,717	921	495
Wald Chi2 (Prob >chi2)	54.72	41.32	39.51
	(0.000)	(0.000)	(0.000)
Deal-characteristics	Yes	Yes	Yes
Country FE	-	-	-
Year FE	Yes	Yes	Yes
Industry FE	-	-	-
Country-Year FE	No	No	No
Industry-Year FE	No	No	No
Country-Industry FE	Yes	Yes	Yes

Notes: This table depicts results of a Probit model estimated by maximum likelihood. The dependent variable is equal to 1 if the borrower has a credit rating of leveraged and highly leveraged, and 0 if it has investment grade rating (Risky indicator). MDB is a dummy equal to 1 if at least one MDB is involved in the syndication of the loan, and 0 if the syndicate includes only private banks. We control for the deal-characteristics of our baseline model of Table 3, including: Risky, Public, Log of total deal value, Number of tranches, Maturity (in months), Term loan, Euro, Other currency, Deal with a guarantor, and Syndicate concentration. All specifications also include year, and country*industry fixed effects. The model is estimated for the baseline sample (1994-2015), as well as for the pre-crisis (1995-2007) and post-crisis (2008-2015) periods. Standard errors clustered at the country and year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data sources: Dealogic Loan Analytics.

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